Identifying the vulnerable forests of Southeast Asia, and transforming them into a conservation and climate change mitigation priority

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Declaration

I declare that this thesis has been composed solely by myself and that it has not been submitted, either in whole or in part, in any previous application for a degree. Except where otherwise acknowledged, the work presented is entirely my own.

Keiko Nomura
July 2019

Abstract

Facing the threat of climate change, preventing land use change in tropical forest areas has been identified as one of the main strategies to reduce carbon emissions to the atmosphere. However, the rate of tropical forest loss has increased rather than decreased over the recent decades, questioning the effectiveness of current approaches in bringing about the necessary changes. To obtain better forest protection and ensure a reduction in emissions, new approaches need to be explored. In Southeast Asia, forest loss is particularly pronounced due to the dominance of agriculture and plantation forestry. The region has experienced a total loss of 11.3% of its forest cover since the beginning of the 21st century, and the rate of loss shows little sign of slowing. Therefore I use Southeast Asia as a case study to present a pragmatic approach to identify and measure forests at risk from deforestation. My aspiration is to develop an approach applicable to the region, which can then be easily adapted globally.

I present three core chapters in this thesis. After the introduction, in Chapter 2, I examine whether the current international incentive-based mechanism to reduce emissions from deforestation and forest degradation (REDD+) is well suited to identify historically vulnerable forests, and whether it is likely to lead to real emission reductions. First, I identify and measure the current areas of forests under REDD+ in the Asia and Pacific region. I compare the benchmark emissions from forests ('reference levels') submitted by the governments to the United Nations Framework Convention on Climate Change (UNFCCC) with forest area change estimates using the Global Forest Change v1.4 (GFC) dataset. The

results show consistent differences, with most countries reporting considerably less historic forest loss than the GFC-based analysis. These differences are due to: the countries' selection of activities to report; as well as their choice of forest types and land use; and the selected definitions of the forests to be monitored. Therefore, even if REDD+ is successfully implemented, it will not necessarily lead to emission reductions.

In Chapter 3, I identify these vulnerable forests and the drivers of deforestation. I use publicly available satellite data (Sentinel-2) to map 13,330 ha in southern Myanmar. This area is a mixed landscape combining large areas of both natural forest and commercial plantations (mostly of oil palm and rubber). I use Google Earth Engine as a data analysis platform to conduct supervised land cover classifications using a machine learning algorithm. The classifier is able to detect the differences between visibly similar tree crops (e.g. oil palm, rubber, betel nut, and forests) with high accuracy (95.5% - 96.0%) at a 20 m resolution. Based on the results of this initial study, I then scale up the analysis to all of southern Myanmar (more than 4 million ha) and add radar (Sentinel-1 and the Shuttle Radar Topography Mission) datasets. The classifier successfully map the region, achieving a high overall accuracy of 94% against an independent test dataset (84-96% and 81-95% accuracy for oil palm and rubber respectively).

In Chapter 4, the method presented in Chapter 3 is used to identify and estimate the area that is actually planted with oil palm within oil palm concession areas in southern Myanmar. The distinction between plantations and concession areas matter, as plantations have been already deforested and converted to oil palm or rubber. Meanwhile, concessions have been allocated to oil palm production, but have yet to be converted. My results show that only 17% of the total concession areas has so far been planted with oil palm (15%, 75,000 ha) or rubber (2%, 7,800 ha). Furthermore, my analyses show that approximately 25,000 ha of oil palm are planted outside formal concessions. This highlights an urgent need to clearly demarcate and enforce concession boundaries. It also reveals that about 200,000 ha of unconverted forests still exist within oil palm concessions that are at high risk of conversion in the future. Hence, these unconverted forests represent an ideal target for conservation and legal protection.

The application of this approach for other regions and crop types could result in substantial protection of forests and carbon stocks. For example, in Kalimantan, Indonesia alone, more than three million ha of intact forests are estimated to lie inside oil palm concessions, mostly with little to no legal protection. It is therefore crucial to understand why some concessions remain unexploited, and to evaluate the possibility of changing the status of these areas to protect the forests. This would not affect current levels of production, yet it could considerably contribute to mitigating climate change.

Overall, the methods developed and findings presented in my thesis offer a route for countries to improve their forest protection plans and reference levels. If implemented across the tropics, this approach could significantly aid policy makers in developing and implementing policies that reduce the loss of forest carbon stocks. I conclude that risk-based approaches considering tree location, land use and legal status, rather than narrowly defined forest areas, could offer a more transparent means for forest conservation, and a better route to achieving the overarching objectives of climate change mitigation.

Lay Summary

Over the past decades, deforestation has led to a large decline in forest carbon stocks globally. Southeast Asia has lost 11.3% of its tropical forest cover since the beginning of the 21st century. Much of the forest was logged for timber and replaced with agricultural crops such as oil palm and rubber plantations. Conversion to agriculture releases a large amount of carbon to the atmosphere: for tropical countries, the emissions from such deforestation greatly exceeds their emissions from burning fossil fuels in power stations and road vehicles. If not protected, emissions from forests will continue to increase and climate change mitigation strategies will not be able to limit the temperature increase. In order to achieve the carbon emission reduction, there is an urgent need to address the effectiveness of current climate change mitigation strategies and propose ways to improve forest protection and resulting emission reductions.

The objective of this thesis is to develop improved methods of identifying forests at risk from deforestation, focusing on Southeast Asia but with the aim of designing approaches suitable for global application. In order to do so, I first evaluate the international mechanism to reduce emissions from forests, called REDD+ (reducing emissions from deforestation and forest degradation, conserving and enhancing forest carbon stocks, and managing forests sustainably in developing countries). REDD+, established by the United Nations Framework Convention on Climate Change (UNFCCC) in 2007, provides financial incentives for emission reductions from forests by assessing the countries' performance against historical emission levels. I compare the data submitted by the countries

in the Asia and Pacific regions to the UNFCCC against an independent global tree cover dataset ('Global Forest Change v1.4'). The results show that countries restrict their forest areas extensively based on their forest definitions, creating a risk of excluding vulnerable forests.

Based on the findings above, I propose a practical method to identify vulnerable forests in Southeast Asia, using Myanmar as a case study. Understanding the data and resource limitations faced by many countries in Southeast Asia, I focused on using publicly available data and a free web-based application programming interface, Google Earth Engine. I used optical satellite data (Sentinel-2) to map land cover in complex forest landscapes containing oil palm and rubber plantations in southern Myanmar. Using a machine learning algorithm, classifications produced highly accurate maps of land cover types (overall accuracy rates 95.5-96.0%) and identified the changes over a two-year period.

I scaled up this method by including radar data (Sentinel-1 and the Shuttle Radar Topography Mission) to identify the total area planted with oil palm within oil palm concessions in Southern Myanmar. With a high overall accuracy of 94%, the results show that only 17% of the total areas designated as concessions have indeed been planted with oil palm (15%, 75,000 ha) or rubber (2%, 7,800 ha). Crucially, I identify 200,000 ha of unconverted forests which still exist within oil palm concessions that are at high risk of conversion in the future.

I argue that protecting these unconverted forests within agricultural concessions should be a priority for climate change mitigation. The application of this approach for other regions and crop types could result in substantial protection of forests and carbon stocks.

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I'd like to thank Dr Edward Mitchard for his guidance and confidence in my ability to undertake this research. He always treated me as his equal and respected my opinions, and helped me tremendously with his depth and breadth of knowledge. I'd also like to thank Dr Genevieve Patenaude for giving me an opportunity to study in Edinburgh and guiding me through the complexities of logic and research questions. My gratitude also goes to the Japan Student Services Organization for funding my study. Owning to this supportive environment, I was able to acquire knowledge, skills, and expertise that will change the course of my career and hopefully the way forests are managed and protected in the future.

I was fortunate to have had opportunities to work with distinguished scholars and researchers globally through my research: Dr Matthew Hansen from the University of Maryland; Mr Peter Iversen from the United Nations Framework Convention on Climate Change; and Dr Sam Bowers from the University of Edinburgh. My fieldwork in Myanmar was not possible without generous help from Mr Mark Grindley from Fauna and Flora International, Dr Alex Diment from WCS, Mr Patrick Oswald and Dr Joan Bastide from OneMap Myanmar, Mr Zaw Win, Ms Thazin Nwe from WWF, and Ms Phyu Phyu San from FAO. I'd also like to thank my former colleagues from the UN-REDD Programme, Dr Timothy Boyle, Ms Celina Yong, Ms Sirin Wannawong, Dr Joel Scriven, and Mr Franz-Eugen Arnold for their continuous friendship and support.

Pursuing PhD was not an easy decision for me. My former supervisor and colleague (as he prefers to be called) in United Nations Environment, Dr Thomas

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"Policies are made in air conditioned rooms"

Vu Thi Bich Hop, Centre for Sustainable Rural Development, Vietnam

"I'm making a decision! Stop confusing me with facts!"

Abbreviations

API	Application Programming Interface
FREL	Forest Reference Emission Level
FRL	Forest Reference Level
GFC	Global Forest Change
GIS	Geographical Information Systems
Gt CO_2e	Gigatonne of CO_2 equivalent
Ha	Hectare
MMU	Minimum Mapping Unit
NDC	Nationally Determined Contribution
NDVI	Normalised Difference Vegetation Index
NERC	Natural Environment Research Council
NIR	Near-infrared
PA	Producer's Accuracy
Pg C	Petagram of Carbon
PNGFA	Papua New Guinea Forest Authority
PRF	Permanent Reserved Forests (Malaysia)
REDD+	Reducing Emissions from Deforestation and forest Degradation, and foster conservation, sustainable management of forests, and enhancement of forest carbon stocks
RGB	Red, Green, Blue
S1	Sentinel-1 Satellite
S2	Sentinel-2 Satellite
Tg CO_2e	Teragrams of CO_2 equivalent
UA	Users's Accuracy
UAV	Unmanned Aerial Vehicle
UNFCCC	United Nations Framework Convention on Climate Change
VH	Vertical transmission; Horizontal reception
VV	Vertical transmission; Vertical reception
WV3	WorldView-3

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Chapter 1

Introduction

1.1 Thesis context

Tropical forests for climate change mitigation

Tropical forests contribute to reducing the impacts of increasing anthropogenic greenhouse gas (GHG) emissions. They store and sequester atmospheric carbon through the processes of photosynthesis: about one sixth of the carbon dioxide released by human activity into the atmosphere each year ends up stored in tropical tree biomass as a result (Karsenty et al., 2003; Pan et al., 2011; Mitchard, 2018). Globally, forests store about 861 petagrams of carbon (Pg C), 55% of which is found in tropical forests (Pan et al., 2011). Between 1990 and 2007, forests represented a net carbon sink of 1.1 Pg C per year, the balance of much larger gross fluxes caused by deforestation and forest degradation releasing carbon, and tree growth taking in carbon (Figure 1.1). However, since the beginning of 21st century, tropical forests have suffered the highest level of deforestation globally: for 2001 to 2012 the losses (1,105,786 km^2) have far exceeded gains (247,233 km^2) for the same period (Figure 1.2) (Hansen et al., 2013). According to Pan et al., 2011, emissions from deforestation amount to 10.3 Gt CO_2/yr between 2000 and 2007. If deforestation continues, and as climate change increases temperatures and the frequency and severity of extreme weather events, tropical forests will become carbon sources rather than sinks (Mitchard, 2018).

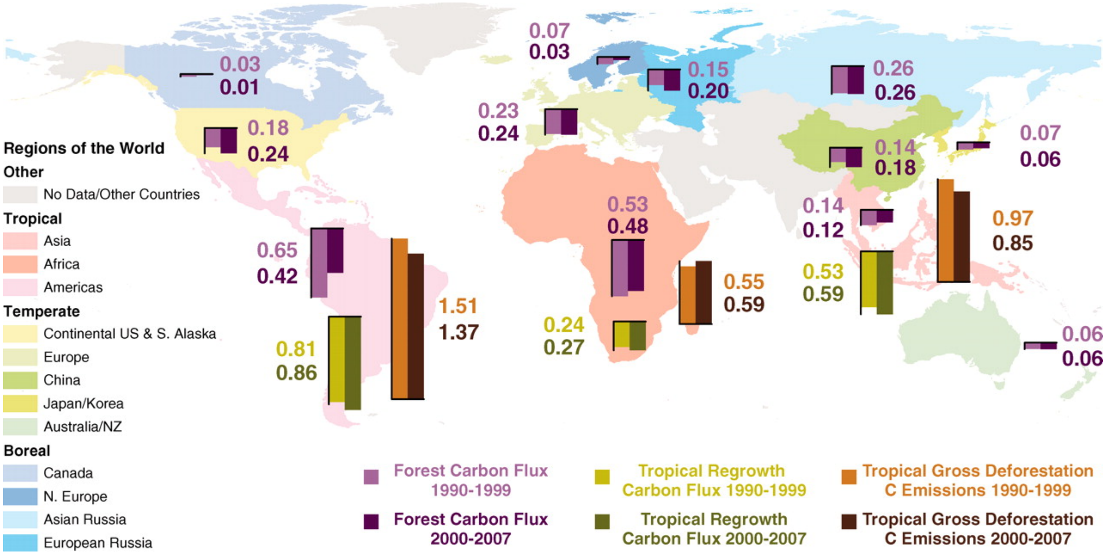


Figure 1.1: Carbon sinks and sources (Pg C year[1]) in the world's forests. Colored bars in the down-facing direction represent C sinks, whereas bars in the upward-facing direction represent C sources. Light and dark purple, global established forests (boreal, temperate, and intact tropical forests); light and dark green, tropical regrowth forests after anthropogenic disturbances; and light and dark brown, tropical gross deforestation emissions. Taken from Pan et al., 2011

Recognizing the importance of forests as carbon sinks, protecting and restoring forests became part of climate change mitigation strategies to limit global warming to well below 2°C above pre-industrial levels ("Paris Agreement") (UNFCCC, 2015; UNEP, 2015). Under the Paris Agreement, a majority of developing countries with significant forest cover included forest sector commitments in their plans ('Nationally Determined Contributions; NDCs') (Petersen and Varela, 2015; Brown et al., 2019).

However, in order to limit warming to 2°C, or better still 1.5°C, by 2030, total emissions should be 25% or 55% lower than those of 2017, respectively (UNEP, 2018). Not only are the current commitments from NDCs inadequate to achieve

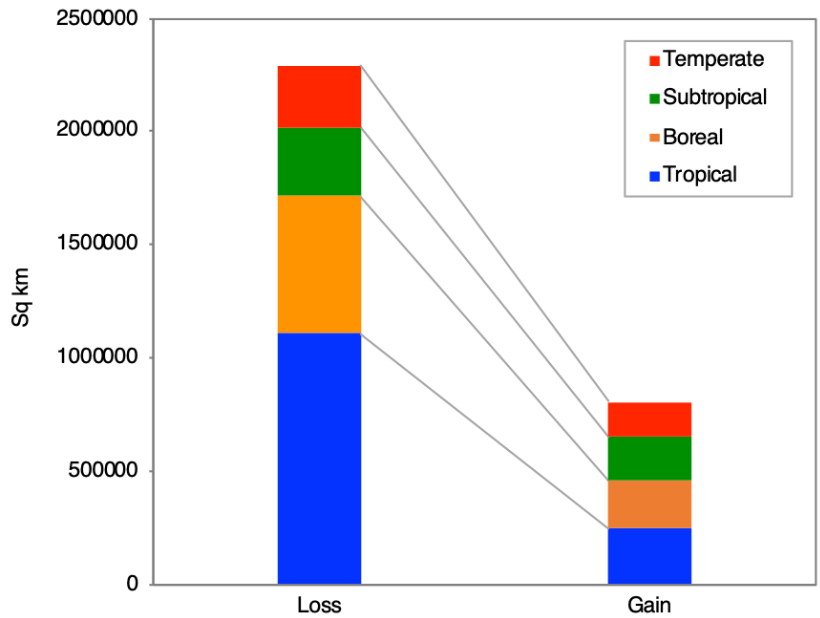


Figure 1.2: Global tree losses and gains (km^2) for the 2001-2012 period, segregated by forest type. Data from Hansen et al., 2013

such ambitious reductions, but they are instead likely to allow an increase in emissions beyond 2030, implying global warming of about 3°C by 2100 (UNEP, 2018). Even if NDCs were fully implemented, the emission gap to achieve the 1.5°C target remains as high as 29 Gt CO_2e in 2030 (UNEP, 2018).

In order to fill this large gap, efforts to reduce emissions need to be combined with removing emissions with forest cover. According to Lewis et al., 2019, in order to limit global warming below 1.5°C through increasing forest area, 24 million hectares have to be added every year from now until 2030. Based on the current restoration commitments by 43 countries, a greater amount of carbon can be stored if natural forests are regenerated (36 Pg C) with the highest potential from Southeast Asia (9.73 Pg C) and Middle Africa (7.73 Pg C) (Figure 1.3) (Lewis et al., 2019). However, the amount will be reduced by 97% if only forest plantations were used (Lewis et al., 2019). Furthermore, deforestation and forest degradation will offset the gain by releasing carbon if existing forests are not protected. Therefore, it is crucial to understand the impacts and implications of current climate change mitigation strategies in order to accelerate the reduction of carbon emissions from forest change.

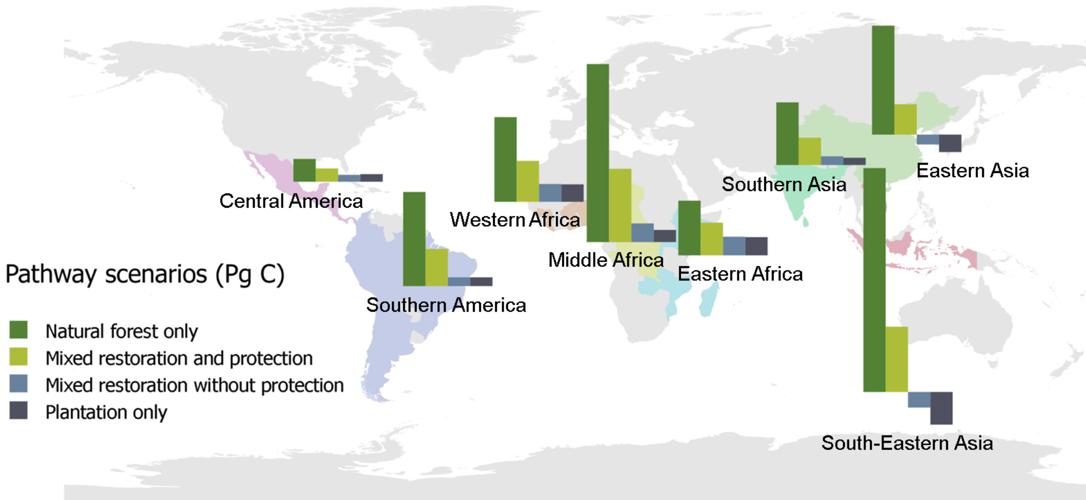


Figure 1.3: Carbon sequestration for four modelled restoration pathways based on national commitments from 43 countries. In South Eastern Asia, the greatest sequestration is achieved if only natural forests are included, whereas if plantations alone are included, the sequestration is negative, i.e. planting this much area with plantations will actually release more carbon than it will take in from the atmosphere. Data from Lewis et al., 2019

REDD+

REDD+ (reducing emissions from deforestation and forest degradation, conserving and enhancing forest carbon stocks, and managing forests sustainably in developing countries) is an important part of efforts to protect forests and fight against climate change. The concept was officially recognised at the Bali Conference of the Parties of the United Nations Framework Convention on Climate Change in 2007 (UNFCCC, 2007). REDD+ provides result-based payments for emission reductions from forests based on the countries' performance against historical emission levels. Today, 39 countries have submitted their benchmark emissions from forests in order to participate in REDD+ and adhere to the rules and methodologies set by the UNFCCC decisions (UNFCCC, 2019). A key limitation to the approach is that historical emissions are based on different methodologies, the scope and scale of activities selected by countries, which may or may not be associated with significant emissions in the country (Melo et al., 2018). In order to achieve the target under the Paris Agreement, there is an urgent need to address the effectiveness of current REDD+ activities and propose ways to maximise its impacts on emission reductions.

Drivers of deforestation in Southeast Asia

The tropical forests of Southeast Asia are the third largest in the world, containing large stores of vegetative and soil carbon and several global biodiversity hotspots (Myers et al., 2000). Over recent decades, the region lost large amounts of forest carbon stocks: the rate of deforestation relates closely to the volume and price of global commodities such as palm oil and rubber (Zeng et al., 2018; Imai et al., 2018; Stibig et al., 2014; Grogan et al., 2019; Curtis et al., 2018; Angelsen and Kaimowitz, 1999). Southeast Asia is the largest global producer of palm oil and rubber. In 2017 alone, it produced 86% and 71% of palm oil and rubber respectively (FAO, 2019). As a result of conversion to agriculture, Southeast Asia lost 17.4 million ha of forest cover between 1990 and 2000 (Stibig et al., 2014) and 29.3 million ha between 2000 and 2014 (Zeng et al., 2018) (Figure 1.4). The carbon loss is the highest of all tropical regions: nearly twice as much, per hectare, as other regions (Figure 1.5) (West et al., 2010). In addition, the region has the highest rate of habitat loss, yet less than 10% of forests have legal protected status (Sodhi et al., 2010). Despite this, a disproportionately small number of proposed REDD+ interventions are in the agriculture sector (Figure 1.6) (Salvini et al., 2014).

To design effective policy interventions to reduce emissions from land use change, it is essential to accurately ascertain the drivers of deforestation and forest degradation. However, during the early efforts of REDD+ readiness, little

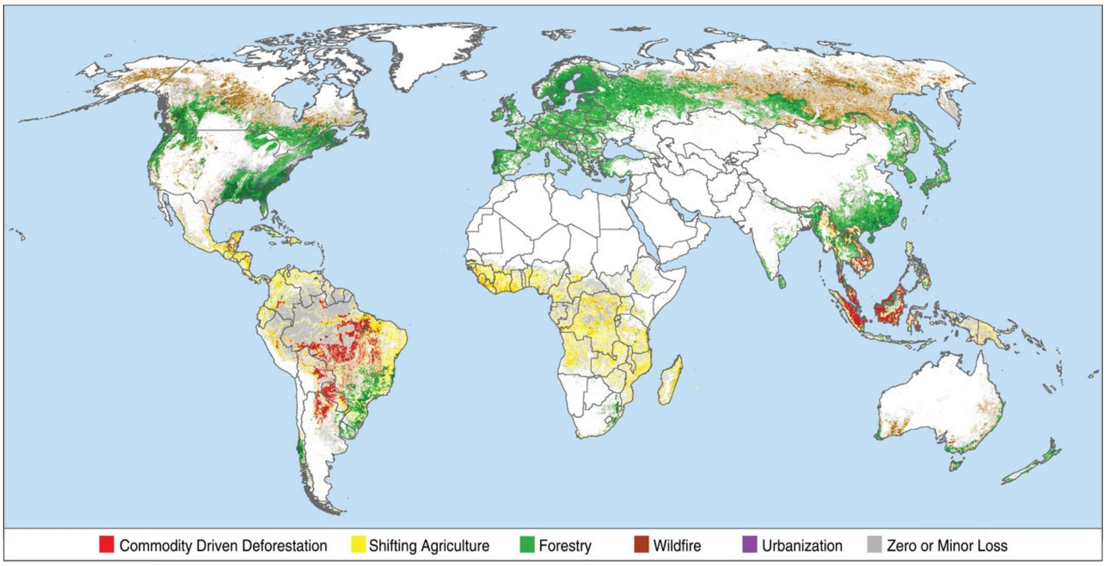
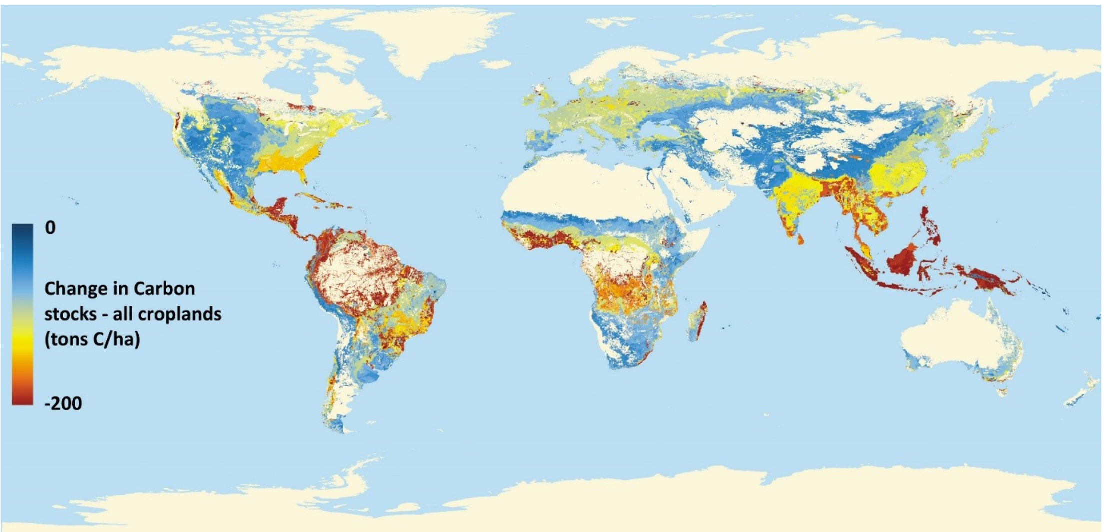


Figure 1.4: Primary drivers of forest cover loss for the period 2001 to 2015. Darker colour intensity indicates greater total quantity of forest cover loss. The forestry class maps sourcing regions for the global forest products industry. Taken from Curtis et al., 2018



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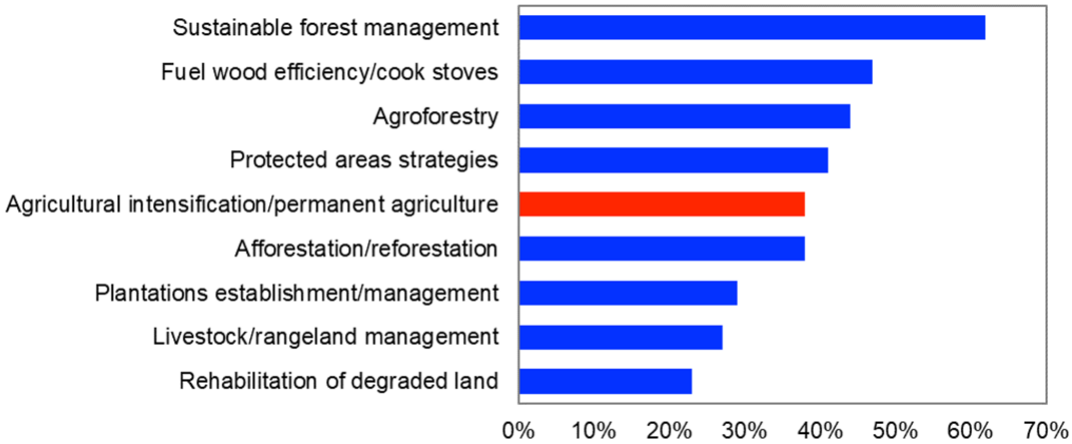

Figure 1.6: Direct REDD+ interventions proposed by 43 countries studied. 38% of the countries included interventions in the agriculture sector. Data from Salvini et al., 2014

attention has been given to assessing those drivers (Visseren-Hamakers et al., 2012; Minang and Noordwijk, 2013). The lack of debates, notably between 2006 and 2010, on the identification of key drivers found in salient REDD+ countries is evident (Di Gregorio et al., 2015). One study showed that more than 30% of the countries proposed interventions without referring to drivers (Salvini et al., 2014). While the most popular intervention was sustainable forest management (68%), the countries whose interventions were linked to drivers proposed agricultural intensification and fuel wood efficiency as their choice of interventions (Figure 1.6) (Salvini et al., 2014).

While more studies on drivers have been conducted under national REDD+ processes since then (e.g. Salvini et al., 2014; Weatherley-Singh and Gupta, 2015), the difficulty and complexity of the problem in addressing drivers has been recognised in many papers on deforestation and land use (Murdiyarso et al., 2012; Salvini et al., 2014). The studies typically rely on interviews, existing literature and sporadically available statistics, resulting in a growing list of drivers, including both direct drivers (e.g. infrastructure expansion) and indirect drivers (e.g. demographic factors) (Geist and Lambin, 2002; Meyfroidt and Lambin,

2011) (Figure 1.7). However, due to multiple drivers and their interactions, and data availability and reliability, the outcomes of the studies had limited impacts. Some authors argue that this arises from a political problem, as addressing real drivers will challenge existing power structures and economic interests that sustain business as usual (Murdiyarso et al., 2012). A potential risk is a deliberate disconnect between identification of drivers and policy design, where a politically weak driver such as shifting cultivation may be targeted even if the assessment revealed that a politically and financially stronger driver such as commercial agriculture is the major cause of deforestation (Dwyer and Ingalls, 2015).

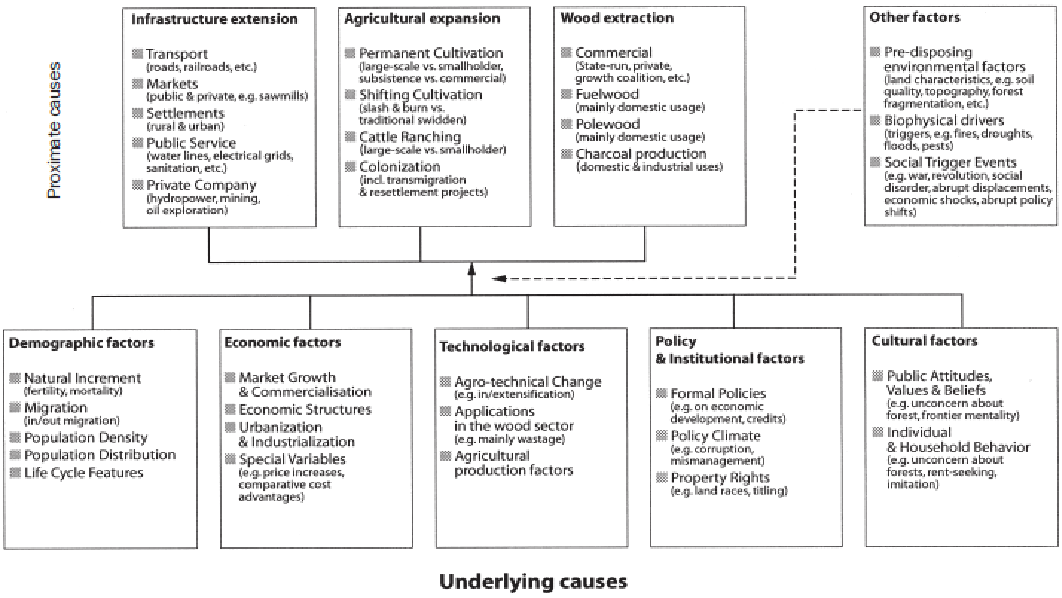

Figure 1.7: Direct (proximate) or and indirect drivers (underlying causes) of forest decline. Taken from Geist and Lambin, 2002

Remote sensing

Beyond policy priorities, a key reason that drivers are often not considered is that the available data on what causes deforestation is poor. Remote sensing has been successfully applied in mapping deforestation (Hansen et al., 2013), but explaining causality ('direct driver of deforestation') depends on reliably detecting what the land is used for after such clearance has taken place. There are two types of satellite data that are normally used to identify land use/cover classes: optical and radar remote sensing data. Optical data have been most widely available spatially and temporally, since 1972, namely through the Landsat program (Woodcock et al., 2008). Radar data are less abundant, but the use of microwave technology has advantages over optical data, as they are not subject to interference by clouds and can penetrate forest canopy to obtain information about forest structure (Woodhouse, 2005; Mitchard, 2016). With the increasing availability of free and high resolution images from satellites such as Sentinel-1 (radar) and Sentinel-2 (optical), both of which provide high revisit time (5-12 days), there is potential for better and more timely land classification today.

Therefore, we now have the data to use remote sensing techniques to identify the direct drivers of deforestation in a consistent manner through change detection and land use/land cover classification. In order to understand what happens to land after deforestation (i.e. drivers of forest loss), local-level classification is necessary due to the varying drivers of deforestation (e.g. a variety of agricultural crops). However, the literature on REDD+ revealed that many developing countries do not have adequate data or resources to conduct such analyses. Furthermore, classifying land in Southeast Asia can be challenging, as the average size of farm declined from 2.5 hectares in 1950 to one hectare in 2000 due to population growth and the dominance of smallholders (Lowder, Skoet, and Raney, 2016; FAO, 2013). Developing remote sensing methods that are economically viable yet accurate, and accessible by many users globally is desirable and needed to create effective policies to reduce deforestation.

In order to explore these themes further, and develop solutions, this thesis focuses on Southeast Asia, and in particular the southern part of Myanmar. The Southeast Asian region was chosen for its high rate of forest loss and diversity of deforestation drivers (Zeng et al., 2018). Myanmar was highlighted because it is in an earlier stage of development and deforestation than its neighbours, and therefore its deforestation rate is very high but the country still has comparatively high forest cover. This offers an opportunity for early interventions before all the potential sites for agriculture have been cleared.

Status of forests and oil palm development in Myanmar

Myanmar has one of the highest deforestation rates in the world. While the country lacks accurate data on deforestation, forest degradation and forest carbon stocks, it is estimated that Myanmar had the third largest absolute area of forest loss in the world after Brazil and Indonesia, an extraordinary figure given it is 2.8 times smaller in area than Indonesia (Figure 1.8)(FAO, 2015). Between 2010 and 2015, Myanmar lost on average 546,000 ha per year (FAO, 2015). According to the RS-GIS Division of the Myanmar Forest Department, forest cover declined from 51% in 2005 to 46% in 2010 and 43% in 2015 (Kissinger, 2017). Between 2005 and 2010, the loss of closed forests (defined as forests with >40% of canopy cover) was particularly acute, at an average rate of 4.7% per year. While recent studies attempt to provide more accurate data on forest cover and forest cover change (Connette et al., 2016; Treue, Springate-Baginski, and Htun, 2016), the academic literature on Myanmar's forests is limited.

Agribusiness concessions have been one of the main drivers of deforestation and forest degradation in Myanmar (Treue, Springate-Baginski, and Htun, 2016; Woods, 2015; Raitzer, Samson, and Nam, 2015). The total area committed as concessions increased from 790,000 ha in 2010-2011 to 2.1 million ha in 2012-2013 (Woods, 2015). The increase of agricultural and temporarily cropped area matches the forest area decline of about 7.7 million ha between 1990 and 2011 (Raitzer, Samson, and Nam, 2015). The expansion of rice cultivation has been the dominant direct driver of deforestation in mangrove forests in the Ayeyarwady Delta. There, the deforestation rate was particularly high at 2.62% along with the high carbon release rate of 2.38% between 2001 and 2010 (Wang and Myint, 2016). Oil palm plantations have increased by 900% since 2000 and are predominantly

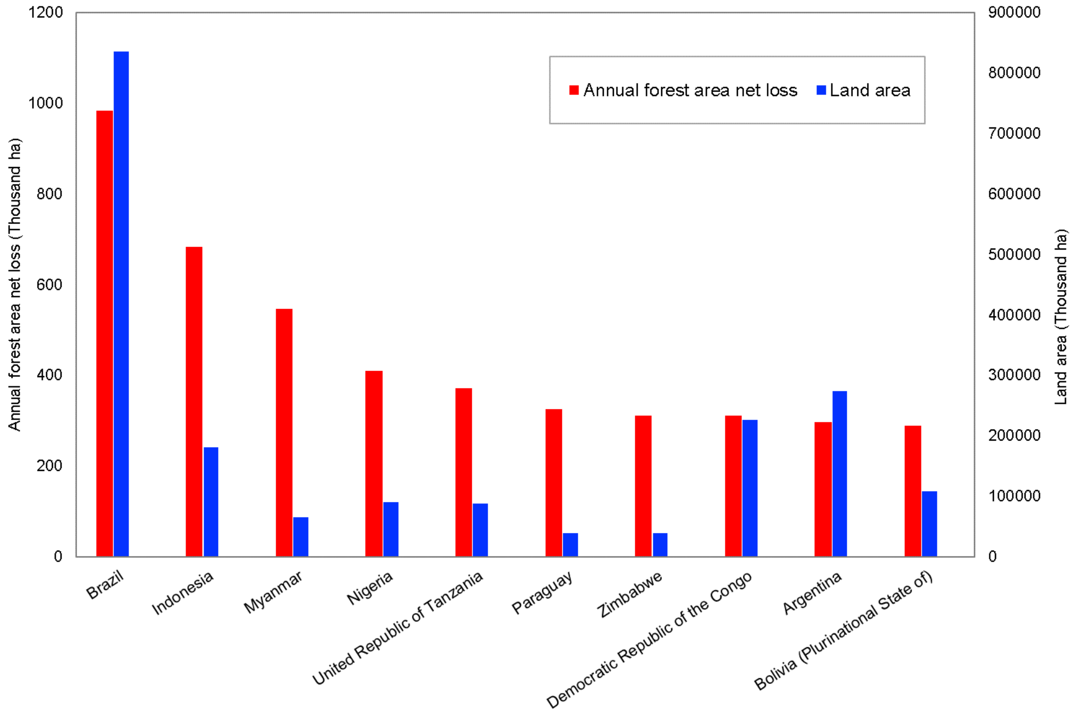

Figure 1.8: Top ten countries reporting the greatest annual net loss of forest area, 2010–2015 and total land area. Data from FAO, 2015; *World Bank Open Data* 2019

located in southern Myanmar, the Tanintharyi Region. The region has the largest total area allocated for oil palm developments (about 400,000 ha). By 2013 and 2015, 19% (Woods, 2015) and 35% (Baskett, 2016) of oil palm concessions were reported to have been planted. Despite constraints such as a large water deficit during the dry season and low sunshine hours in the wet season, the region is deemed suitable for oil palm (Baskett, 2016). According to the oil palm concession licence agreement, if the land was not cleared within four years after the licence is issued, it will be cancelled and a fee will be charged (Baskett, 2016). However in practice, such rule was rarely enforced, and the company can retain the land if it provides an explanation for noncompliance. Furthermore, some companies mainly planted oil palm along the road for visibility reasons, giving an impression of a large-scale plantation (ALARM, 2018).

Attempts at mapping forests and agricultural land in Tanintharyi using land

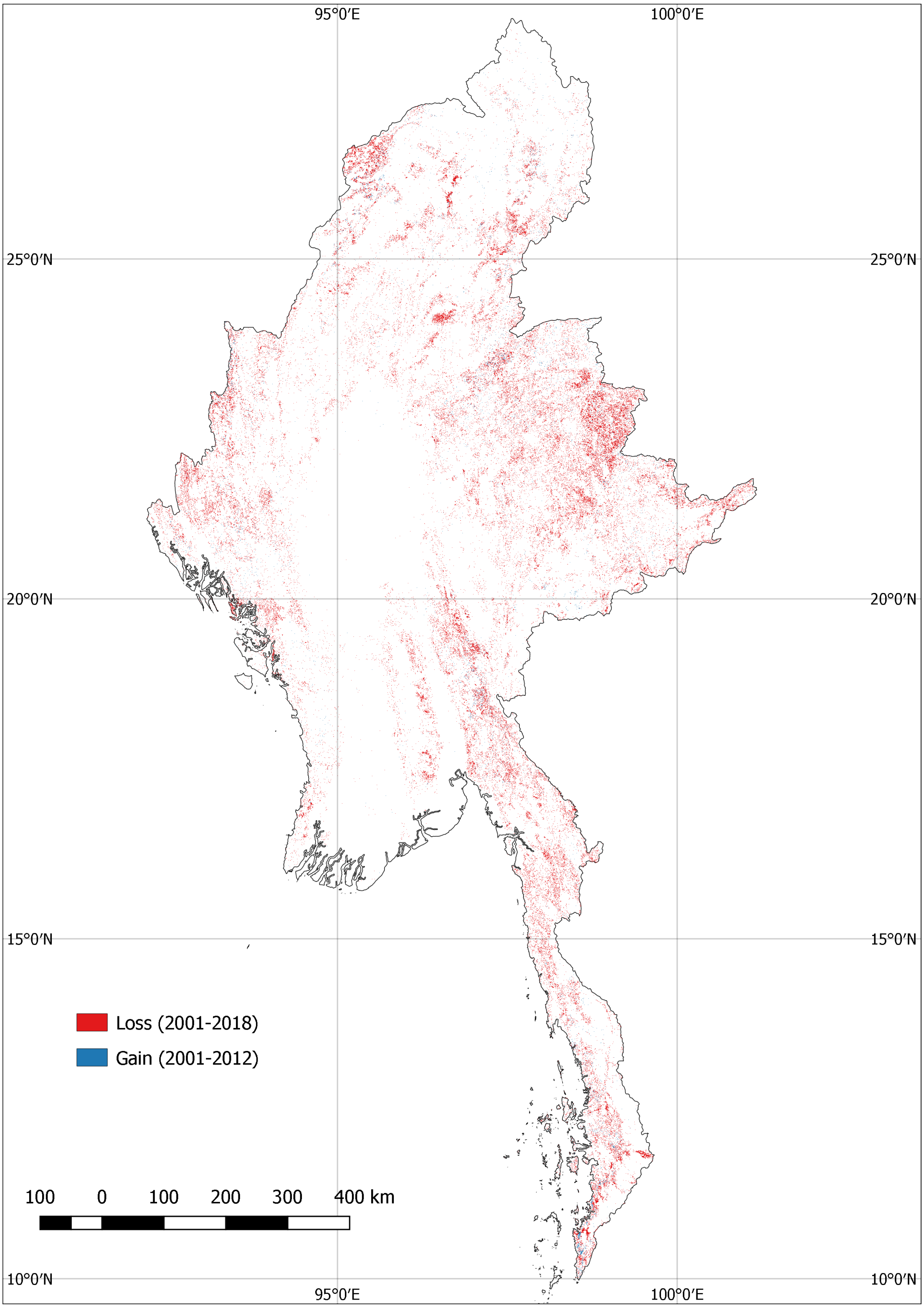

Figure 1.9: Myanmar map showing tree loss (red, 2001-2018) and gain (blue, 2001-2012). Data from Hansen et al., 2013

classification methods exist (Connette et al., 2016; Bhagwat et al., 2017; De Alban et al., 2018; Poortinga et al., 2019). However, the area estimates per class vary significantly by study (125,000 ha (2018) to 620,000 ha (2015)), so do their accuracy rates (overall accuracy rates from 74% to 94% with the lowest per class user's accuracy rate at 41%) (Connette et al., 2016; De Alban et al., 2018; Bhagwat et al., 2017; Poortinga et al., 2019).

The current approaches to reducing emissions from forests were established through UNFCCC decisions. However, their impacts and effectiveness, particularly in targeting drivers of deforestation, haves not been examined. Furthermore, a lack of quantitative data on drivers has not been addressed with alternative methods that cater for developing countries with limited resources. As a result, there is an increasing risk of implementing interventions with a weak link to the main emission sources.

1.2 Thesis objectives and overview

The objectives of this thesis are three-fold: to understand the implications of current approaches; to propose practical methods to identify direct drivers of deforestation using publicly available spatial data; and to identify whether any potential 'quick win' areas for conservation are available that are not being considered. Specifically, I ask the following research questions:

1. In Southeast Asian and neighbouring countries, how much (and what kind of) forests are covered under the international climate change mitigation mechanism, REDD+?

2. In Myanmar, can we accurately ascertain direct drivers of deforestation by classifying land after deforestation in these complex forest-agriculture-plantation landscapes?

3. In Myanmar, using the case study of the nascent oil palm industry, can we

identify forest at risk and estimate the scale of potential areas available for conservation but currently set aside for future conversion?

This thesis comprises five chapters. Chapter 1 sets the scene and explains the urgency and rationale for the research. The next three chapters are each stand-alone peer-reviewed publications (two published and one undergoing peer-review at the time of submission). These chapters correspond to the three stages in answering research questions (see Figure 1.10). I also present an appendix which contains my fieldwork report, from a trip to Myanmar in 2017 and an in-depth assessment of the sites and the region studied for Chapter 3 and 4. Chapter 5 summarises the findings and discusses the implications and wider application of the results as well as the limitations and further research areas.

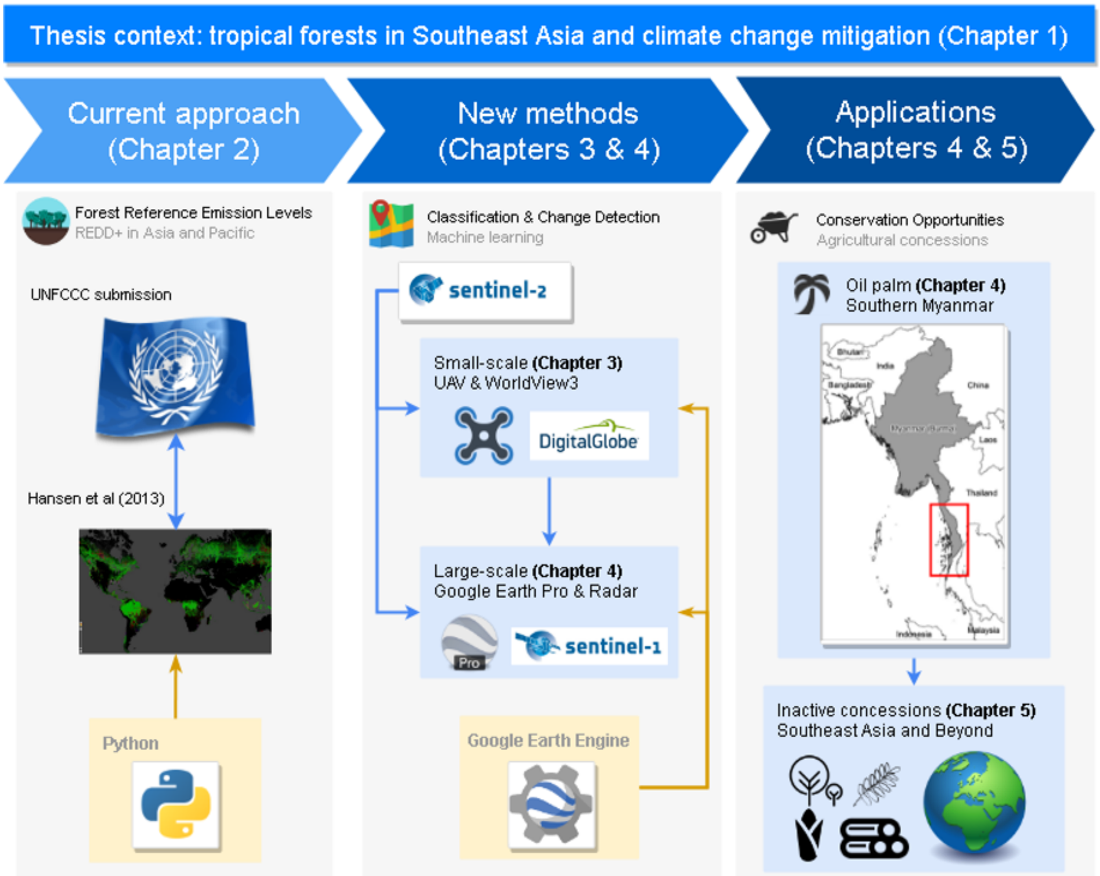

Figure 1.10: Overview of thesis structure

Chapter 2: Missed carbon emissions from forests: comparing countries' estimates submitted to UNFCCC to biophysical estimates

The emission reductions from forests are measured by establishing reference levels for the future based on historical forest cover data. The main objective of the paper is to identify linkages and gaps between the trend of tree cover change created by using a remotely-sensed and independent dataset and the estimates used by the governments for potential REDD+ payments in Asia and the Pacific. The analysis was conducted based on the countries' submissions to the UNFCCC as of December 2017. Specifically, I address the following questions:

- What constitutes a forest and which of the REDD+ activities are selected by countries?
- How are the historical emissions calculated in the reference level submission? What are the implications of data sources and timeframe used?
- What are the trajectories of forest cover change using the independent dataset 'Global Forest Change v1.4'? How different are they from the governments' estimates used to establish reference levels for the submissions to the UNFCCC?

Chapter 3: More Than Meets the Eye: Using Sentinel-2 to Map Small Plantations in Complex Forest Landscapes

The current application of remote sensing techniques to identify changes in land cover and land use face many challenges for complex landscapes involving small parcels and similar tree crop types. We propose a simple method using publicly available data and a free web-based API (Google Earth Engine) to conduct classifications to capture the changes in land cover, which can be used to identify direct drivers of deforestation. We selected two study sites in southern Myanmar, which exhibit typical regional characteristics in terms of crop types and the size of plantations in Southeast Asia. I addressed the following hypotheses in this paper:

- Pixel-based machine learning classification of Sentinel-2 data can be used to map complex forest landscapes with high accuracy, as an alternative to computationally-intensive object-based classification methods.
- Changes in land area by class from year to year can be confidently measured.

Chapter 4: Oil palm concessions in southern Myanmar consist mostly of unconverted forest

Oil palm production in Southeast Asia is well established as a driver of deforestation based on the relationship between the increase of plantations and decrease of forests. Vast intact forests were evidenced to have been replaced with oil palm plantations. It has been suggested elsewhere however that potentially large areas of awarded oil palm concessions are left unplanted. Given these, I addressed the following questions:

- How can the method used in Chapter 3 be scaled up to classify a large area?
- How much of the oil palm concession areas are currently planted or left unplanted?
- Which crop is more dominant in southern Myanmar, oil palm or rubber?
- What are the implications for the forests remaining in current concessions?

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Chapter 2

Missed carbon emissions from forests: comparing countries' estimates submitted to UNFCCC to biophysical estimates

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Abstract

Reducing forest loss has the potential to reduce global carbon emissions, but paying countries to do so will only work if activities are targeting areas with rapid deforestation or high threat. As of December 2017, 25 countries reported their benchmark greenhouse gas emissions from forests ('reference levels') under the United Nations Framework Convention on Climate Change, with the aim of receiving payments if they end up releasing less or removing more. There remains however a question as to whether the eventual emission trajectories compared to these reference levels represent real emission reductions, as the benchmarks rely on a variety of different methods and limited datasets. To examine whether the forest areas historically associated with significant emissions are targeted in the reference levels, we compared the forest area estimates submitted by seven countries in Asia and the Pacific (Cambodia, Indonesia, Malaysia, Nepal, Papua New Guinea, Sri Lanka, and Vietnam) with forest area estimates using the Global Forest Change v1.4 (GFC) dataset from 2000–2016, processed to closely match national forest definitions. GFC provides standardised tree cover change data based on biophysical characteristics using an extensive collection of satellite images. We found consistent differences, with most countries reporting considerably less forest loss than the GFC-based analysis. These differences are due to the countries' selection of activities to report, as well as their choice of forest types and land use, defining the forest areas to be monitored. Our study highlights an urgent need to address the gap between the forests monitored by countries and those sources of emissions. The current approaches, even successfully implemented, may not lead to emission reductions, thereby challenging the effectiveness of carbon payments.

2.1 Introduction

As of end 2017, 25 countries had submitted their benchmark emission levels from forests to the United Nations Framework Convention on Climate Change (UNFCCC, 2017). These benchmarks, called 'forest reference emission levels' or 'forest reference levels' (hereafter both referred to as 'reference levels') are established to assess countries' performance in activities pertaining to Reducing Emissions from Deforestation and forest Degradation, plus the sustainable management of forests, and the conservation and enhancement of forest carbon stocks (thereafter referred to as REDD+) with the aim of them receiving significant, results-based payments for their emission reductions. However, very few studies have analysed the potential impacts on deforestation or emission reductions based on the contents of these submitted reference levels (Hargita, Gunter, and Kothke, 2016; Mertz et al., 2018). More attention has been paid to the governance and policy aspects, and recent studies focused on small-scale REDD+ projects between NGOs and communities and their socio-economic impacts in the short term (Mbatu, 2016).

Our study aims to assess the effectiveness and impacts of planned activities for reducing or removing emissions from forests by comparing forest areas presented in the reference level submissions ('country-defined REDD+ forests') to biophysical forest areas calculated with the Global Forest Change v1.4 ('GFC') dataset ('biophysical forests') (Hansen et al., 2013). REDD+ forest areas are defined and constrained by each country's scope of REDD+ activities, national definitions of forests, and land use classification. Although the definitions include biophysical parameters as a threshold (e.g. minimum canopy cover), they exclude areas that meet such parameters if the land use class is not forests (e.g. agricultural land). This potentially excludes any remaining forests that had been allocated for other land use but have not yet been cleared (e.g. agricultural concessions) (Carlson et al., 2013; Zoological Society of London, 2017).

In order to obtain a comprehensive picture of the trajectory of emissions, however, it is necessary to examine biophysical changes on the Earth's surface, commonly referred as land cover change, as compared to land use change, which is defined by the purpose for which humans use land (e.g. for agricultural or residential purposes)(Lambin, Geist, and Lepers, 2003). The GFC dataset presents time-series analyses of satellite images, and provides tree canopy data (trees are defined as vegetation >5 m in height). The GFC dataset can be used to track changes in forest areas globally in a consistent manner. Here, we processed the GFC dataset to match the biophysical parameters used in each country's forest definition and how the changes are recorded in calculating the reference levels.

Greenhouse gas fluxes are the results of tree removal, degradation, and regrowth (Baccini et al., 2017; Mitchard, 2018; Rappaport et al., 2018). Therefore, the changes in the biomass of trees within a country are critical for emissions, and land use and forest definitions act to remove a proportion of these trees from consideration, meaning that changes in land use do not always reflect changes in forest areas (Houghton and Hackler, 2003; Verburg, Neumann, and Nol, 2011; Houghton et al., 2012). Therefore, it is possible that the underlying data for the reference levels do not capture the full emissions from the changes in the biomass. In this study, by using the reference levels submitted by countries in the Asia-Pacific region in 2017, we examined whether submitted 'Country-defined REDD+ forests' represent the main source of emissions from tree loss within each county.

2.2 Data and methods

2.2.1 Forests under REDD+ ('Country-defined REDD+ forests')

Seven countries in Asia and the Pacific region were considered, and their forest areas ('country-defined REDD+ forests') were extracted from the reference level submissions to the UNFCCC ('UNFCCC Submissions') by the end of 2017

(UNFCCC, 2017). These are Cambodia (Cambodia, 2017), Indonesia (The Ministry of Environment and Forestry, Indonesia, 2016), Malaysia (Ministry of Natural Resources and Environment, Malaysia, 2015), Nepal (Ministry of Forests and Soil Conservation, Nepal, 2017), Papua New Guinea (Government of Papua New Guinea, 2017), Sri Lanka (Sri Lanka UN-REDD Programme, 2017), and Vietnam (Ministry of Agriculture and Rural Development, Vietnam, 2016). All the seven countries went through the technical assessments by the UNFCCC and subsequently modified submissions. For our study, we focused only on 'Activity Data' in the UNFCCC Submissions, which contains historical forest area change or deforestation data.

We calculated the changes in country-defined REDD+ forests as a difference between forest areas in 2000 and 2010, except for Cambodia where the applicable national data were available for their reference period starting from 2006.

Scope and definition

In the UNFCCC submissions, the countries selected which of the five REDD+ activities were to be undertaken ('scope'), defined what constitutes a forest in terms of minimum canopy cover, tree height and area size, and established whether there are land uses that include trees that are not considered as forests (e.g. plantations) (Table 2.1).

All countries within our selection, except Malaysia, included 'reducing deforestation' in their scope for REDD+. Malaysia elected instead to consider 'sustainable management of forests' only, which generally refers to the adaptation of methods to reduce the impact of timber harvesting practices (GOFC-GOLD 2013). Another noteworthy difference between the countries is that some included plantations in their forest definition. Indonesia excluded all types of plantations, while Cambodia and Sri Lanka excluded rubber plantations. Forest plantations were included by all but Indonesia.

	Forest definition							Scope				
	Minimum				('X' = included)			Reducing emissions		Removal of emissions		
	Canopy cover (%)	Tree height (m)	Forest area (ha)	Loss and/or gain area (ha)	Forest plantation	Rubber plantation	Agricultural land (including oil palm)	Deforestation	Forest degradation	Conservation of forest carbon stocks	Sustainable management of forests	Enhancement of forest carbon stocks
Cambodia	10	5	0.5	25, 5	X			X	X			X
Indonesia	30	5	6.25	6.25				X	X			
Malaysia	30	5	0.5	0.5	X[a]						X	
Nepal	10	5	0.5	2.25	X	X		X	X			X
Papua New Guinea	10	3	1	1	X	X		X	X			X
Sri Lanka	10	5	0.5	0.5	X			X				X
Vietnam	10	5	0.5	0.5	X	X		X	X			X

Table 2.1: The countries' elected forest definition and their proposed scope for change (summarised from UNFCCC Submissions as of 2017)[2]. Please also consult Tables S1 and S2. [a]Production forests in Permanent Reserved Forests (PRF) only.

[2]Please note that the technical assessment process by the UNFCCC resulted in removing other activities initially proposed by some countries due to technical and accuracy reasons.

Activity data

Within these scope of activities and forest definitions, forest area change (referred as 'Activity Data' in the UNFCCC submissions) was estimated. The Activity Data includes the amount of forest area change or deforestation during the historical period selected ('reference period'), which is used as a benchmark for assessing countries' performance in implementing the selected REDD+ activities. The reference periods among the seven countries varied from eight to 22 years with the earliest starting year of 1990 and the latest of 2006 (Table 2.2). The number of actual data points in the reference period also had a wide range, from 2 to 23. If a country believes that the historical rate does not reflect the likely changes in the future, adjustments can be made with justifications (Government of Papua New Guinea, 2017; Ministry of Agriculture and Rural Development, Vietnam, 2016).

In generating Activity Data, the commonly used method is wall-to-wall mapping and detecting changes by comparing classified maps (e.g. Cambodia, Indonesia, and Vietnam) (Table 2.2). This method, however, can lead to substantial errors because each map inevitably contains some errors, which will be compounded when comparing two maps to detect changes (FAO, 2018). In correcting the effects of classification errors, two countries (e.g. Nepal and Sri Lanka) used a stratified area estimation approach, which distributes a sample of reference data in a stratified manner based on the classes. The disadvantage of this method is that statistically derived area estimates may no longer match with the areas on maps (FAO, 2018). Papua New Guinea is the only country that used a systematic sampling method, which is more transparent, as samples are distributed in a non-stratified manner, but it requires a large number of samples to achieve reliable results (FAO, 2018). The highest overall accuracy rates in mapping were reported by Indonesia (98%) and Vietnam (95%) and the lowest by Cambodia (74%) and Sri Lanka (75%). Forest gain data had much lower

	Reference period	Method	Data source[a]	Overall accuracy (forest, non-forest)
Cambodia	2006, 2010, 2014	Wall-to-wall mapping	LANDSAT	74% (2006), 85% (2010)
Indonesia	1990, 1996, 2000, 2003, 2006, 2009, 2011, 2012	Wall-to-wall mapping	LANDSAT, SPOT Vegetation, MODIS	98% (2011)
Malaysia	1990–2012	Based on reporting validated with remote sensing data	Annual Reports of the Forest Department; National Commodity Statistic Report	N/A
Nepal	2000, 2010	Wall-to-wall mapping, stratified area estimation	LANDSAT	86% (2000), 87% (2010)
Papua New Guinea	2001–2013	Systematic sampling	LANDSAT 7 and 8, Google Earth, Bing Maps	N/A[b]
Sri Lanka	2000, 2010	Wall-to-wall mapping, stratified area estimation	LANDSAT, GFC	75%
Vietnam	1995, 2000, 2005, 2010	Wall-to-wall mapping	LANDSAT, SPOT 4 and 5	95% (2010)
GFC v1.4	2000–2016	Direct change detection with automatically pre-processed satellite data	LANDSAT	99.5%-99.8% (2000–2012)

Table 2.2: Reference period, methodology, data, and accuracy for Activity Data. [a]Not including the data used for training or validation purposes. [b]Papua New Guinea conducted the accuracy assessment for the 2015 map (89%).

accuracy rates with 68% by Nepal and 9% by Sri Lanka (Ministry of Forests and Soil Conservation, Nepal, 2017; Sri Lanka UN-REDD Programme, 2017).

Based on the Activity Data, the reference level is calculated with emission factors in tonnes of CO_2 equivalent per hectare per year ('forest reference emission levels'), or net emissions ('forest reference levels', which include removals). From this, payments can be calculated if future monitoring suggests a positive deviation from the reference levels. Therefore, excluding certain activities or the way in which forests are defined affects the reference level, and future carbon payments significantly. For example, a decline or increase of plantations in Indonesia will not affect their performance in emission reductions, but the loss of natural forests will matter greatly; while in Malaysia loss of any forests other than their target production forests is not relevant to potential carbon payments.

Estimating forest area for the study

Indonesia selected only deforestation in the scope of REDD+, therefore we estimated the forest cover by calculating the forest gain from the GFC v1.4 dataset using the national definition for minimum change area (Table 2.3). Indonesia's loss for 2010 was estimated by using the average of 2009 and 2011 loss data, as deforestation data were not provided for 2010. Papua New Guinea reported there was no forest gain during the reference period. The loss data for Papua New Guinea were directly estimated from the figure 7.4: Deforestation occurred in PNG 2000–2013 (PNGFA Collect Earth Assessment) (Government of Papua New Guinea, 2017). Sri Lanka reported forest loss and gain between 2000 and 2010, but chose not to report the forest areas estimated in constructing the reference level. Therefore, we used the 2010 forest area reported in the Forest Resource Assessment 2015, and applied loss and gain data from the UNFCCC Submission to estimate the forest area for 2000 (FAO, 2015; Sri Lanka UN-REDD Programme, 2017).

A few countries used different minimum area size from their forest definition when detecting the changes: Cambodia used a minimum mapping unit (MMU) of 25 ha for 2006/2010 and 5 ha for 2014 and Nepal used a 2.25 ha MMU in detecting

	Minimum							
	Canopy cover (%)							
	Cover and loss	Gain	Tree height (m)	Forest area (ha)	Loss and/or gain area (ha)	Forest plantation	Rubber plantation	Agricultural land (including oil palm plantations)
Cambodia		10	5	0.5	25 (2006-2010), 5 (2014)	Forest	Not forest	Not forest
Indonesia	30	50 (GFC)[a]	5	6.25	6.25	Not forest	Not forest	Not forest
Malaysia		30	5	0.5	0.5	Forest[b]	Not forest	Not forest
Nepal		10	5	0.5	2.25	Forest	Forest	Not forest
Papua New Guinea	10	n/a (no gain)	3	1	1	Forest	Forest	Not forest
Sri Lanka	10	50	5	0.5	0.5	Forest	Not forest	Not forest
Vietnam		10	5	0.5	0.5	Forest	Forest	Not forest

Table 2.3: Biophysical parameters and forest types for country-defined REDD+ forests. Indonesia's forest gain data were supplemented from GFC for the study. [a] Only deforestation estimates were reported in the UNFCC submission, thus we supplemented with forest gain from GFC using the national definition (see section Tree gain). [a]Production forests in Permanent Reserved Forests (PRF) only.

changes in country-defined REDD+ forests, while both countries used 0.5 ha for the minimum forest area (Table 2.3). For Indonesia, Papua New Guinea, and Sri Lanka, we assumed that the countries used the same minimum forest area size to detect changes, which is 0.5 ha for all except Papua New Guinea (1 ha). It should also be noted that the minimum tree height for Papua New Guinea was 3 m, while others were 5 m.

2.2.2 GFC-based forest areas ('biophysical forests')

In estimating biophysical forest areas, the GFC v1.4 dataset was processed to match the forest definitions for minimum canopy cover, minimum area, and minimum mapping areas for change detection in the reference levels (Table 2.4). The GFC dataset defines trees as all vegetation taller than 5 m in height and directly detects changes on land cover using an extensive collection of pre-processed Landsat satellite images. Using hierarchical classifiers ('decision tree'), tree canopy cover (for the year 2000) are produced in 30 m Landsat pixels with high accuracy (>99.5% for loss and gain at tropical and subtropical climate domain scales) (Hansen et al., 2013). While loss is provided per annum, gain is reported as a total for the 2001–2012 period and considered as pixels where tree cover increases to >50% canopy cover.

	Minimum canopy cover (%)		Minimum tree height (m)	Minimum area (ha)	
	Forest cover and loss	Gain		Forest	Change (loss and gain)
Cambodia	10	50	5	0.5	5
Indonesia	30	50	5	6.25	6.25
Nepal	10	50	5	0.5	2.25
Papua New Guinea	10	50	5	1	1
Sri Lanka	10	50	5	0.5	0.5
Malaysia	30	50	5	0.5	0.5
Vietnam	10	50	5	0.5	0.5

Table 2.4: Biophysical parameters used to extract biophysical forest areas using the GFC dataset.

Similar to country-defined REDD+ forests, a difference between forest areas in 2000 and 2010 was calculated, except for Cambodia, where the difference was calculated between 2006 and 2010. Cambodia used two different MMU (25 ha for 2006/2010 and 5 ha for 2014) in detecting the changes in their forests. However, in processing the GFC data, we used a 5 ha MMU for Cambodia throughout the respective period to measure the changes consistently. Due to the tree height definition in the GFC dataset, the 5 m minimum height was assumed for all seven countries including Papua New Guinea, which selected 3 m in the UNFCCC submission. However, as the tree height definitions were used as assumptions rather than actual measurements in both cases, we don't believe this difference has any notable impact in estimating forest cover.

Tree cover

Forest areas for the year 2000 (2006 for Cambodia) were calculated from treecover pixels, which were required to satisfy the minimum canopy cover requirement, and be connected to other pixels with sufficient canopy cover so as to form a patch of forest larger than the minimum area size (Figure 2.1). The contiguity constraint was applied with a country-specific pixel area calculation, and with pixels connected diagonally (queen's move) included as a single patch of forest.

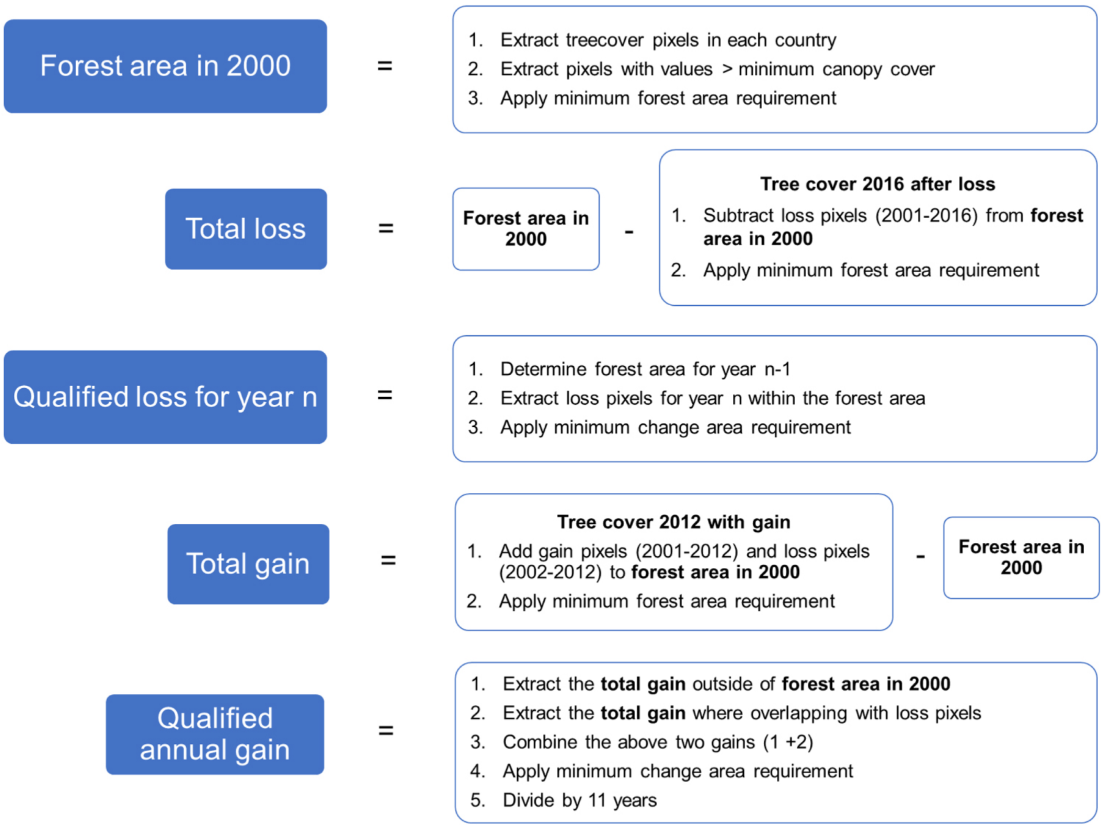

Figure 2.1: Calculation of biophysical forest areas using tree cover, loss and gain from the GFC dataset (see Supplementary Figure A.1 for more information).

Tree loss

For each year thereafter we recalculated forest areas based on the loss of previously forested pixels (Figure 2.1). Loss was recorded in cases where pixels that previously met each country's forest definition were identified as a forest loss for each year from 2001–2016. Treecover pixels were still required to meet the minimum forest area or change area condition, thus loss was also recorded in locations where forests became fragmented to the extent that a forest patch was too small to meet this requirement. In these cases, an area of forest loss was only counted where the contiguous area over which a forest disturbance was recorded was larger than the minimum change area specification.

Tree gain

Increases in tree cover are reported by GFC as a total for the period 2001 – 2012. We therefore calculated the total forest area gain for this period and allocated it uniformly over the measurement period. In a similar manner to losses, forest area increases were subject to minimum forest area as well as a minimum change area requirements, and gains were included in cases where forest patches that previously didn't meet the minimum area requirement increased in size to meet the minimum area size. In cases where the GFC dataset reported a gain at a location that was already recorded as tree cover, pixel areas were not included as part of the gain area. Where both losses and gains were reported at the same location, the gains were assumed to have occurred following loss, so pixels were included in both gain and loss area accordingly (Figure 2.1).

2.2.3 Data availability

GFC data were processed in Python, making particular use of numpy, scipy and gdal libraries. All data and code that support the figures are available; on publication these will be uploaded to an open data repository (See supplementary materials, available online: stacks.iop.org/ERL/14/024015/mmedia).

2.3 Results and discussion

2.3.1 Changes in forest area between 2000-2010

Figure 2.2 shows the changes in forest areas defined in the UNFCCC submissions ('country-defined REDD+ forests') and biophysical forest areas using the GFC dataset ('biophysical forests') in each country from 2000-2010. The decreases in biophysical forest areas were more than reported changes in country-defined REDD+ forests, with the exception of Sri Lanka. The differences are most stark for Malaysia and Vietnam, where country-defined REDD+ forests increased in area through the time period, while their GFC-based forest areas decreased.

The main reasons for differences relate to the type of forests included, the methods used to map forests and forest change, and the type of change processes included. We will consider each in turn.

Area compared

Country-defined REDD+ forest area is less than biophysical forest area in most countries (Figure 2.3, Nepal and Cambodia are the only exceptions). This is because a biophysical forest definition (based on minimum tree cover percentage, height, and area size) will include trees in non-forest land use areas, such as plantations, agricultural land or settlement areas with trees (Table 2.1, Figure 2.3). This could explain the difference of loss in Indonesia for example, where the proportional difference between the rates of loss broadly corresponds to the differences in the area of forests compared (Figures 2.2 and 2.3). However, some countries show unexpected results: Sri Lanka has more forest loss in country-defined REDD+ forests than the changes in biophysical forests; and Nepal and Cambodia have larger areas in country-defined REDD+ forests than biophysical

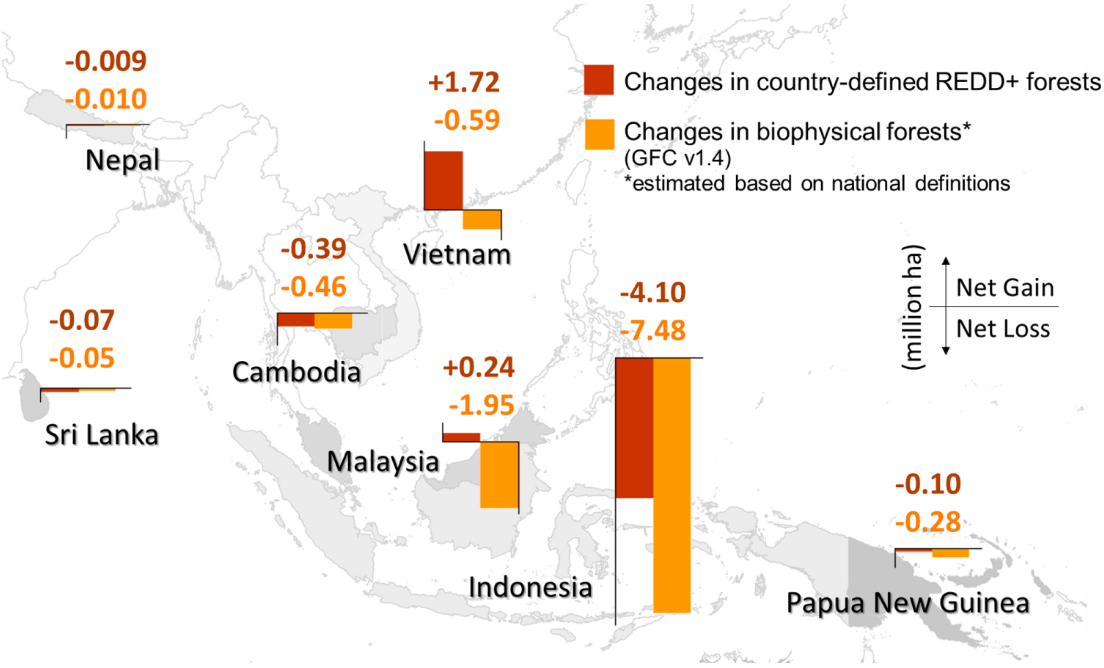

Figure 2.2: Were forests gained or lost? Changes in country-defined REDD+ forests versus biophysical forests in seven countries between 2000-2010 (except for Cambodia 2006-2010, as the applicable national reference period starts in 2006). Biophysical forests refer to GFC data processed according to the national definitions included in the UNFCCC definitions (see section GFC-based forest areas ('biophysical forests')). See Tables 2.3 and 2.4 for the parameters used in the calculation.

forests would predict. In all cases, however, this is likely due to differences in mapping methodology, for which see below.

Mapping methods and accuracy

No mapping methods are free from errors (Table 2.2) (Olofsson et al., 2013). The GFC dataset's overall accuracy using the direct detection method are 99.6% and 99.7% for loss and gain respectively, while the countries selected different mapping methods and the resulting overall accuracy varied significantly from 74% to 98%. For example, Nepal and Sri Lanka used a stratified area estimation method and achieved relatively low accuracy rates (Table 2.2). Especially for Sri Lanka, the

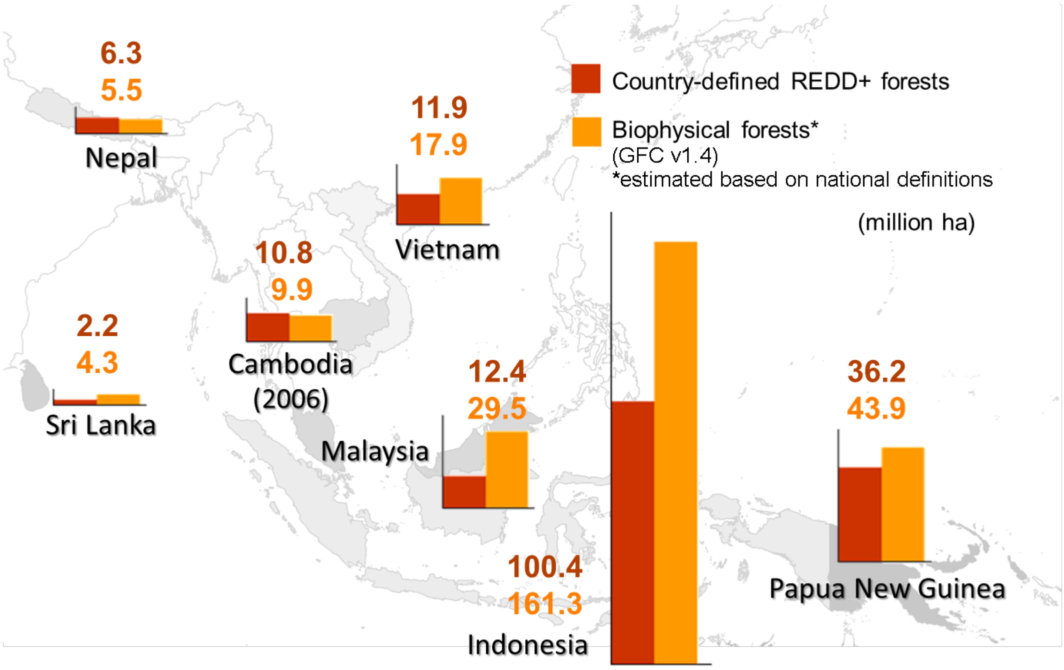

Figure 2.3: How much forest is included in reference levels as compared to biophysical forest areas? Forest areas for the year 2000 from the national UNFCCC Submissions are shown, and compared to those calculated from the GFC dataset using national definitions as per their UNFCCC Submissions (see section GFC-based forest areas ('biophysical forests')). For Cambodia 2006 is used to match the first year of their reference level. Biophysical forests refer to processed GFC data (see section GFC-based forest areas ('biophysical forests')).

accuracy rates for loss and gain were 79% and 9% respectively (UNFCCC, 2018). Cambodia's biophysical forest area in 2006 was estimated with tree cover in year 2000, adjusted with gain and loss data using a 5 ha MMU, while the country-defined REDD+ forests were based on wall-to-wall mapping.

Processes included

The changes in biophysical forest areas using the GFC dataset are blind to the process of change: it is looking at the net change in forest cover over the period, with forest as defined nationally based on canopy cover and minimum area size. However, the dataset includes processes that would under national definitions not be deforestation or reforestation. For example, both the clearance and growth of trees within plantation areas are included in the GFC-based biophysical forests, but not in country-defined REDD+ forests. This likely explains the large difference in change data in Vietnam (Figure 2.2), whose UNFCCC submissions show net forest gain over the 2000-2010 period, when plantations in the country were expanding, while the change in biophysical forests show a large loss as deforestation continued and trees in plantations were harvested (Figure 2.2). This is partially exacerbated by Vietnam's decision to include plantations with tree crop shorter than 5 m, increasing the rate at which forest gain appears to occur. Malaysia shows a similar difference, with its reported net gain largely due to the exclusion of deforestation in the scope of REDD+ activities, and limiting it solely to production forests, which have increased in area over that decade.

One might assume that the differences in change data caused by the harvesting and replanting of plantations would stabilise with time: if the area harvested each year is the same as the area of plantation that reaches the required canopy cover and height threshold, then the impact of plantations on the net change in biophysical forests will be zero, matching country-defined REDD+ forests data. However, as trees are long lived, even in tropical plantations, and planting tends to happen in spurts of a few years related to national programmes and incentives, it may be that such an annual balance of planting and harvesting never occurs. This is further complicated because detecting forest gain in satellite data is much more challenging than the abrupt change in forest loss: therefore the GFC dataset includes only a single layer for gain, stating that an area became forested at some point in the range 2000-2012, meaning our gain data is smoothed compared to the annual loss data; further the gain from the GFC data only detects gains as occurring when trees reach a 50% minimum canopy cover, higher than the thresholds for loss. All plantations will reach this threshold long before harvest, so again this will not ultimately change the net number, but it may be another reason for differences between GFC-derived change in forest areas and national figures.

2.3.2 The rate of change

We further analysed changes in country-defined REDD+ forests in each country's reference period against the annual changes in biophysical forests from 2000-2016, in order to look for trends with time and assess the decisions related to the period chosen by each country (Figure 2.4). It is clear that rates of forest area change vary considerably depending on where the reference period starts and stops; for example had Cambodia's reference period ended in 2010 rather than 2014, the annual average deforestation rate would be 0.9% instead of 2.9%. Cambodia's acceleration in deforestation in 2014 is not just related to the period chosen however: its MMU for forest was changed from 25 ha in 2010 to 5 ha in 2014, created a potential bias toward a higher average rate, as more deforestation was captured (the impacts of different MMUs are discussed further in section 3.3). While this was addressed in the quality assurance stage in the UNFCCC Submission (Cambodia, 2017), the resulting trend appears very different from that of biophysical forest areas using annual data.

Sri Lanka, like Cambodia, shows a relatively larger decline in country-defined REDD+ forests, based on very few data points (just two). We have already discussed the potential issues with Sri Lanka's forest change data (Figure 2.2) and low mapping accuracies, but the difference is large and the tendency here is to predict more loss than in biophysical forest area change.

Indonesia, Nepal and Papua New Guinea in contrast all have a strong correspondence between trends in the two datasets (in contrast to the area based data displayed in Figure 2.2). Indonesia has chosen to use a very long reference period, including the high rates of forest loss from the late 1990s (Figure 2.4(b)) (Margono et al., 2014). This choice potentially allows Indonesia to claim larger

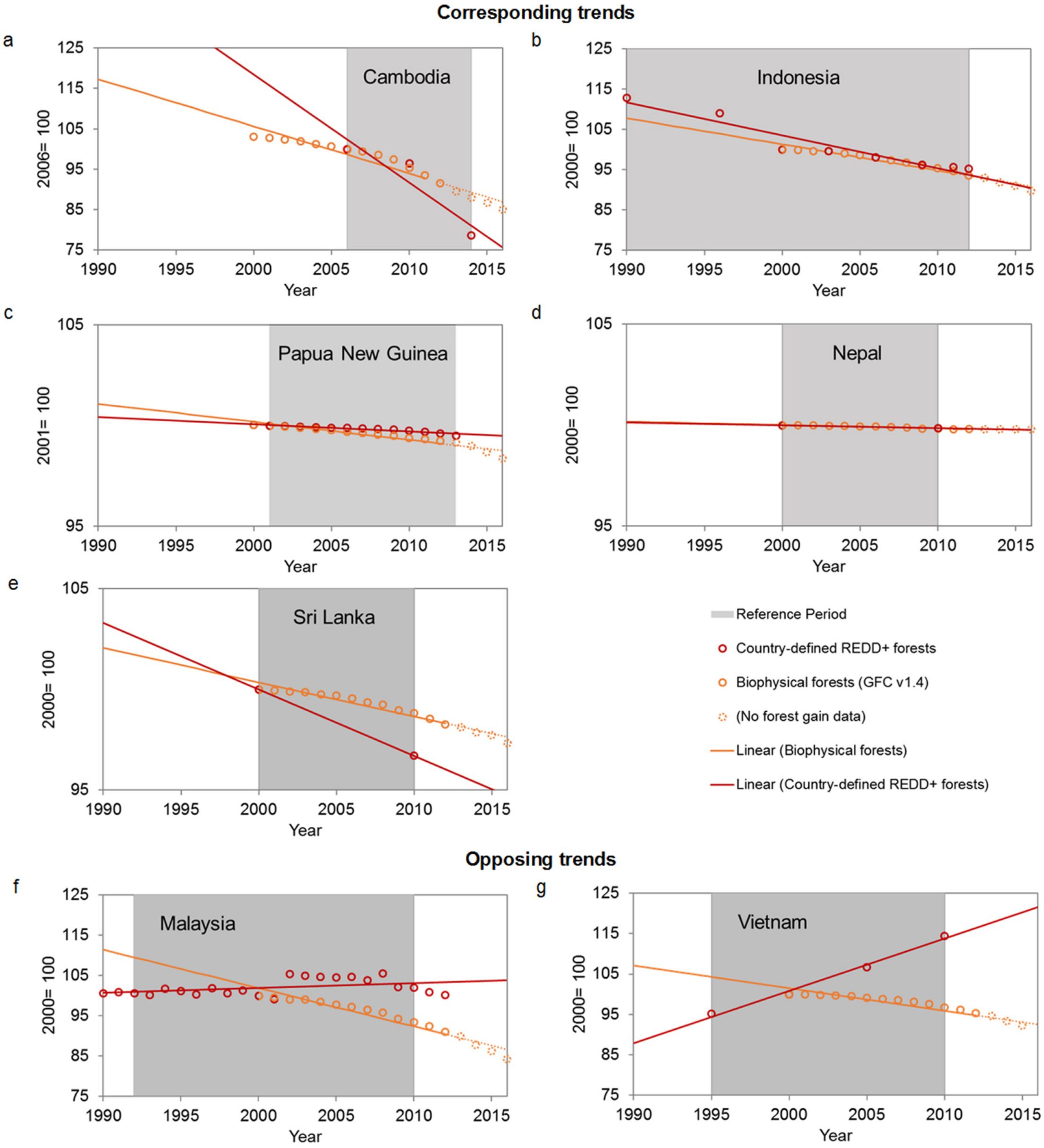

Figure 2.4: Comparing the rates of change in country-defined REDD+ forests versus biophysical forests, where forest areas in 2000 are indexed at 100, except for Cambodia (2006 is indexed at 100) and Papua New Guinea (forest area in 2001 is indexed at 100), as their reference period starts after 2000. The 'Linear' lines are the best fit straight lines representing the data in linear regression. After 2012, biophysical forest areas were calculated with forest loss only (shown dashed lines), due to the availability of forest gain data stopping in 2012. Biophysical forests refer to processed GFC data (see section GFC-based forest areas ('biophysical forests')). See Tables 2.2 and 2.4 in the method section for the parameters used in calculation.

emission reductions against their baseline than if they had chosen a shorter period. At the same time, higher loss rates in country-defined REDD+ forests than in the entire country's forests may indicate that the vulnerable forest areas were effectively targeted for their national REDD+ implementation (Indonesia selected natural forests for REDD+, which is about half of their biophysical forests. See section Forests under REDD+ ('Country-defined REDD+ forests')).

Malaysia and Vietnam, as previously shown in figure 2.2, have opposing trends of change between country-defined REDD+ forests and biophysical forests (Figures 2.4(f)-(g)). Their biophysical forest areas show a consistent annual decline of tree cover over the reference periods. The large area of agricultural land with tree cover in Malaysia (e.g. oil palm or rubber plantations), much of which were planted long before 2000 and thus may have been in the cycle of harvesting from 2000 onwards, may be responsible for some of the difference. However, such impacts would not be sufficient to explain the consistent net decline between 2000-2016. More research is urgently needed to isolate plantation and natural forest changes in these countries. However, it is clear that the limited scope and forest area chosen by Malaysia will mean that even if their UNFCCC submissions are implemented in full, REDD+ in these countries will not mean that forest loss is reduced.

2.3.3 Impact of the minimum area size choice for change detection

Our analysis also indicated that the choice of minimum forest change areas ('MMU') produce sizable differences in reported forest area change. In the UNFCCC Submissions, four countries used MMUs larger than 0.5 ha (Table 2.1), and three countries used MMUs larger than the forest definitions under the Marrakech Accord (0.05-1.0 ha) (UNFCCC 2002). The common reasons given for using larger MMUs are to avoid errors at the single pixel level, or to allow manual visual interpretation of satellite images (Ministry of Forests and Soil Conservation, Nepal 2017). Cambodia and Nepal detected changes using MMUs of 5-25 ha and 2.25 ha respectively, as compared to the minimum area of 0.5 ha used for their forest definition. Indonesia and Papua New Guinea selected 6.25 ha and 1 ha as their minimum forest areas respectively.

We estimated that the impacts of these minimum areas in four countries using the GFC dataset (Figure 2.5). By 2012, loss rates were higher by as much as 40% when using a 0.5 ha MMU. This shows the importance of MMUs, particularly for Nepal where the almost half of total forest loss by area is in polygons smaller than 2.25 ha. These differences result in one million ha of additional forest loss by 2016, which if included would change their reference levels. This suggests a divergence between the reference levels and biophysical reality: the trees are still lost, whether within large or small areas, but are only counted for REDD+ if the area is above a certain threshold size. While this lack of inclusion in reference level does not directly bias payments in the favour of the countries, using similar methods during the implementation of REDD+ could allow small or even medium-scale forest loss to continue without any penalty. It should be noted that we assume such changes are not correctly quantified under the degradation heading—all countries considered here except Malaysia and Sri Lanka do include forest degradation in their scope, but their methods for submitting reference levels and monitoring degradation mean there is a good chance forest clearance events smaller than the MMU would not be accounted for.

2.3.4 Changes in forest area under the uniform forest definition

Lastly, we analysed the rate of forest area change for all countries under the uniform forest definition using the GFC dataset: 10% minimum canopy cover and 0.5 ha for minimum forest area and change area (Figure 2.6).

All seven countries show a declining trend of forest areas, with the largest decline in Malaysia until 2002, and then Cambodia thereafter. By 2012, forest

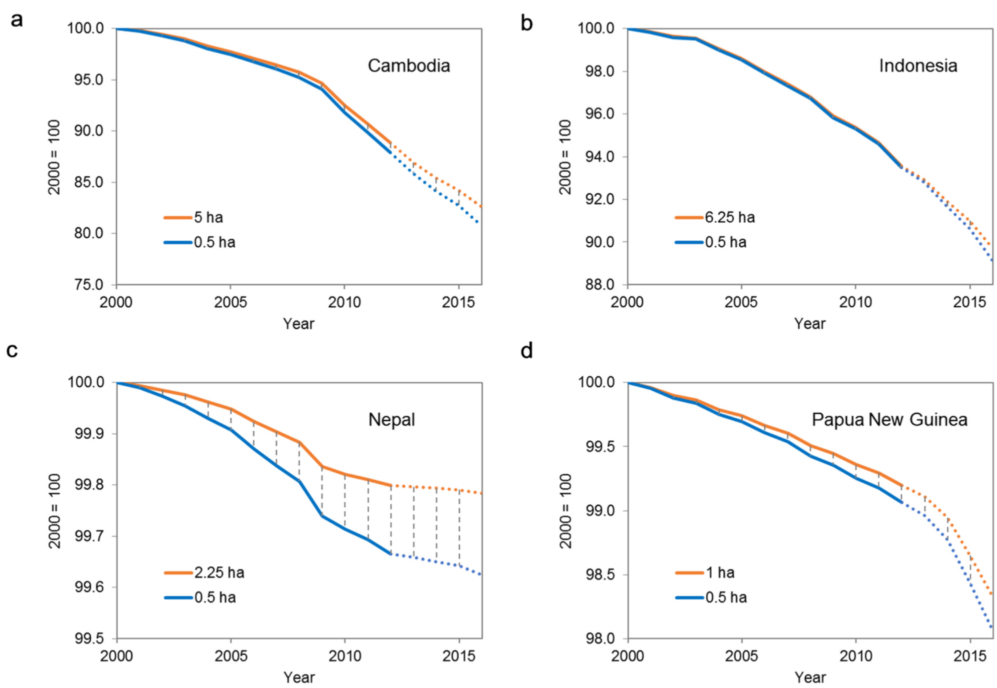

Figure 2.5: Change in forest area under different minimum mapping units (see Supplementary Table A.3 for numbers used in the comparisons) in four countries where the countries used large MMUs (>0.5 ha) to detect changes or to define forest areas. In all cases these are compared to 0.5 ha. After 2012, forest areas were calculated with forest loss only (shown dash lines), due to the limited availability of forest gain data (2000-2012).

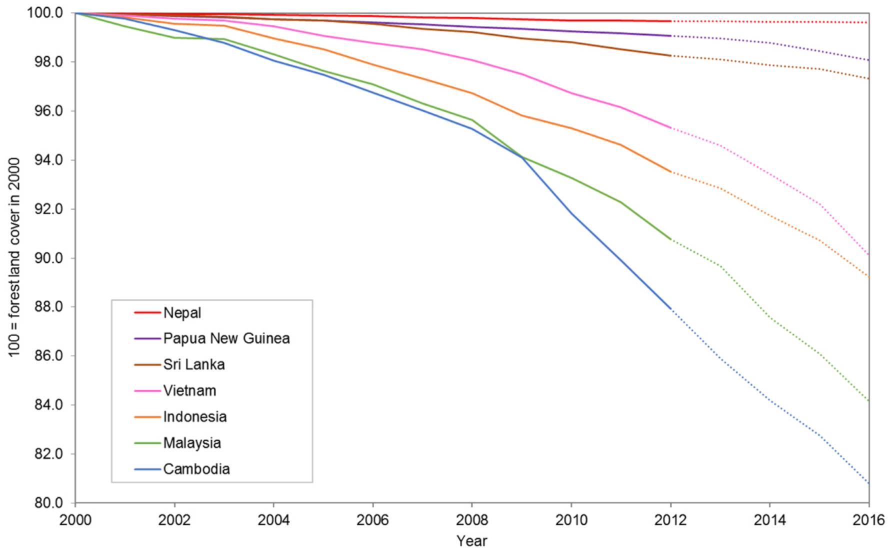

Figure 2.6: Annual changes in forest areas using the consistent forest definition across the countries from 2000-2016 (GFC v1.4). After 2012, forest areas were calculated with forest loss only (dashed lines), due to the limited availability of forest gain data (2000-2012).

areas were reduced by more than 12% in Cambodia and 9% in Malaysia, followed by Indonesia and Vietnam with 5%-6% loss, with some recent evidence of slowing deforestation in Indonesia, relative to the other three countries. While most of the forest areas were retained in Sri Lanka, Papua New Guinea, and Nepal between 2000-2012, Papua New Guinea showed an increasing deforestation trend, especially after 2014 (Figure 2.6). The consistent net loss over the long term is an alarming evidence of emission trajectories in all the countries.

2.4 Implications

Accurately mapping changes in forest cover is essential for understanding the carbon fluxes from tropical forests to the atmosphere (Mitchard, 2018). Arguably of more importance however is the use of such data to set up reference levels for REDD+, in order to predict what would happen to forest area without intervention, and to quantify what has happened in reality following such intervention. If there are biases in the setting of reference levels, caused not just by the use of inappropriate or poorly analysed data, but also by decisions relating to forest and process definitions, MMU, and included land use types, then REDD+ will inevitably be less successful at reducing the rise in atmospheric greenhouse gases.

The annually updated GFC dataset (Hansen et al., 2013) has given us independent and high resolution (30 m) data to map changes in biophysical forest areas, and we here have used this to assess the reference levels contained in the UNFCCC submissions of seven Asian countries. We have found significant differences in the size, and even direction, of changes in forest areas between the GFC dataset (processed to use national definitions), and the country-defined REDD+ forests.

The decisions made as to the duration and starting date of the reference period of these countries clearly impacts the resulting reference levels (Mertz et al., 2018). The availability and quality of data were the main deciding factor in selecting the reference period rather than considerations of accuracy, economic development and drivers. In many cases we have found reference levels appear to underestimate forest change, which poses less of a risk for overclaiming future emissions reductions, but the mismatch still suggests that the drivers are not identified or targeted well in the reference levels. In the case of Cambodia and Sri Lanka, it appears that their reference levels overstate forest loss, resulting in the potential for overclaiming emissions reductions in the future (Figure 2.4).

Furthermore, the selection of activities could pose risks of missing emissions: for example, not including 'forest degradation' in scope can lead to a perverse incentive to allow the degradation of forests to at least partially replace deforestation, in order to assist with achieving the stated goal of reducing deforestation. Clearly this leakage from deforestation to degradation would greatly reduce the benefits of REDD+, though we must emphasise that we have no evidence it is occurring in any of these selected countries. Nevertheless, a case can be made for including as many activities as possible, while keeping monitoring at low cost (e.g. sample based). The reported figures would still have large uncertainties, but at least the removal of trees would be more likely to be quantified, however and wherever it occurred.

A limitation of our study relates to forest change in plantations, the effect of which we cannot quantify as no open maps of plantation area exist for these countries. Our total forest change (including both losses and gains) will inevitably be higher than national datasets, which tend to exclude changes related to harvesting cycles (Hansen et al., 2014; Tropek et al., 2014). Future work on independently assessing reference levels would greatly gain from countries releasing spatial data on national land use classes.

A further, and associated, limitation relates to mapping forest gain, which is in all our analyses uniformly allocated from 2001-2012. More and better forest gain data is desired, and could improve future iterations of this study. However, this would be unlikely to fundamentally change our results, as most of the countries studied experienced far more loss and very little gain according to the UNFCCC Submissions.

Based on the findings of our study, we believe that the process of identifying trends and drivers of forest loss should start with detecting changes at the biophysical level, without initial exclusions based on land use classes. Since the UNFCCC Submissions are typically led by a government department for the forestry sector, there may be limitations in investigating forest loss or identifying remaining forests in other land use class. Allowing countries to define forests within certain guidelines is of course reasonable, but when combined with decisions on the inclusion of production forest and a free rein on deciding which land use classes will be included, and then mapping them, countries can make decisions that will greatly impact their reference levels. The level of freedom currently allowed as regards areas to be included in REDD+ creates a mismatch between countries' potential achievements in REDD+ and emission reductions from forests. It may be that the production of an independent reference level, based on general assumptions, and encouraging countries to justify why their baseline differs from it significantly, could be a useful step. We also stress that in order to achieve protection for all standing trees, it is important to utilise small MMU (certainly less than or equal to 1 hectare) for defining forest and forest change.

2.5 Acknowledgments

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Chapter 3

More Than Meets the Eye: Using Sentinel-2 to Map Small Plantations in Complex Forest Landscapes

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Abstract

Many tropical forest landscapes are now complex mosaics of intact forests, recovering forests, tree crops, agroforestry, pasture, and crops. The small patch size of each land cover type contributes to making them difficult to separate using satellite remote sensing data. We used Sentinel-2 data to conduct supervised classifications covering seven classes, including oil palm, rubber, and betel nut plantations in Southern Myanmar, based on an extensive training dataset derived from expert interpretation of WorldView-3 and UAV data. We used a Random Forest classifier with all 13 Sentinel-2 bands, as well as vegetation and texture indices, over an area of 13,330 ha. The median overall accuracy of 1,000 iterations was >95% (95.5% - 96.0%) against independent test data, even though the tree crop classes appear visually very similar at a 20 m resolution. We conclude that the Sentinel-2 data, which are freely available with very frequent (five day) revisits, are able to differentiate these similar tree crop types. We suspect that this is due to the large number of spectral bands in Sentinel-2 data, indicating great potential for the wider application of Sentinel-2 data for the classification of small land parcels without needing to resort to object-based classification of higher resolution data.

3.1 Introduction

Land use change in the tropics has a significant impact on the carbon cycle, and thus global climate change, but it is poorly quantified (Mitchard, 2018). In mitigating climate change through conserving and enhancing forest carbon stocks, monitoring the changes in land cover and land use provides crucial information for policy development and enforcement in areas such as forest conservation, watershed, and environmental protection (Grassi et al., 2017). While there are sufficient data on deforestation provided by systematic and free-to-use remote sensing (Hansen et al., 2013), what happens to land after deforestation (or the drivers of deforestation) varies by location (Zarin et al., 2016) and there are no global products providing these data, making local classification of the resulting land use necessary for both carbon accounting and policy implementation purposes.

There are a number of ways in which the area of different land cover and land use types within an area, and how they are changing, can be assessed. These range from agricultural census surveys to various types of remote sensing. The most commonly used approaches in the tropics include wall-to-wall mapping using remotely sensed images and/or sample-based approaches for area estimation (FAO, 2018; Bartholome and Belward, 2005; Gibbs et al., 2010; Mayaux et al., 2005). However, classifying landscapes can be challenging in the tropics today, as the average farm size has been decreasing in developing countries (Lowder, Skoet, and Raney, 2016; FAO, 2013). In Asia, this change has been especially pronounced, with the average size of agricultural holdings falling from 2.5 hectares in 1950 to one hectare in 2000, where the fragmentation of holdings driven by population growth is prevalent (Figure 3.1) (FAO, 2013; Masters et al., 2013). More recently, rubber production has shifted from being dominated by large plantations, to being dominated by smallholders in Southeast Asia, resulting in 80% of global rubber production being managed by smallholders with plantations 2-3 ha in size (Deininger, 2011). To overcome the challenge of this decrease in patch size, high spatial resolution images from unmanned aerial vehicles (UAV, ground resolutions typically 1–50 cm) and hyperspatial satellites such as WorldView-3 (WV3, with the highest resolution band at a 31 cm resolution) can be used, which provide detailed visual information on vegetation on the ground. While these images typically feature few spectral bands (normally optical RGB plus potentially one infrared band), limiting their ability to differentiate land cover types based on spectral characteristics, their high resolution enables the human eye to differentiate most land cover types based on, for example, the shape and density of trees, and the advancement of object-based classification methods has meant that automated processes can also take advantage of this spatial information to produce accurate classifications (Li et al., 2015; Feng, Liu, and Gong, 2015; Amini et al., 2018; Su and Zhang, 2017). However, the high costs and complexity of both the object-based image analysis, and the high cost and low availability of data at a sufficient resolution, remain as challenges for wider application (Ma et al., 2017; Georganos et al., 2018).

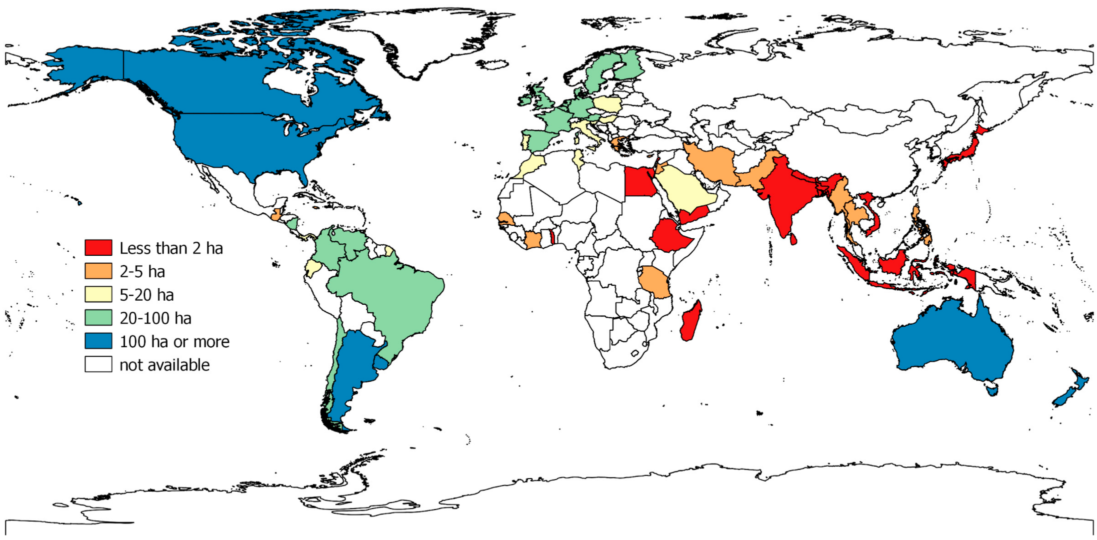


Figure 3.1: Average size of agricultural holding in 2000 (data adapted from Lowder, Skoet, and Raney, 2016).

Our study investigated whether publicly available data, namely Sentinel-2

(S2), can map complex landscapes in Southern Myanmar, including oil palm, rubber, and betel nut plantations using a Random Forest classifier on Google Earth Engine. Unlike UAV and WV3 data, widely available satellite data (which is typically at best a 10–30 m resolution, with the standard platforms of Landsat and S2) cannot be used to visually detect individual trees (Figure 3.2). However, Sentinel-2 has great potential for mapping vegetation types in complex landscapes as it is a multispectral instrument with 13 bands, some of which (for example, the 'red edge' bands) cover very narrow portions of the spectrum, less than 20 nm wide, giving it some of the advantages in classification that were traditionally only available to a true hyperspectral sensor[2]. The resolutions of the bands vary, with four at a 10 m resolution, and the rest at a 20 or 60 m resolution. Taking advantage of the spectral bands with a 10–20 m pixel size, several studies have estimated the extent of land cover types (e.g., cropland, wetland, snow cover) and produced maps of certain forest types (e.g., savanna, deciduous forests) and urban landscapes (Immitzer, Vuolo, and Atzberger, 2016; Xiong et al., 2017; Laurin et al., 2016; Paul et al., 2016; Oliveira Silveira et al., 2017; Topaloglu, Sertel, and Musaoglu, 2016). Furthermore, with a high revisit frequency of five days, agricultural monitoring systems are being developed using Sentinel-2 data, taking advantage of its temporal as well as spectral resolution (ESA, 2018). However, to our knowledge there has been no attempt to classify a landscape with as complex a mixture of small patches of similar tree crops as our study site in Myanmar using S2 data, despite the prevalence of such landscapes across the tropics. This is likely because hyperspatial images are typically used to conduct such classifications (but over small spatial areas, due to limited data availability and the high cost of purchasing/collecting and processing such data). Furthermore, S2 data, along with other satellite data, are generally considered for and associated with broader scale analyses.

[2] A hyperspectral sensor typically contains hundreds of narrow spectral bands (e.g. 255), while a multispectral sensor has several bands. Therefore, the differences between hyperspectral and multispectral sensors are in the number of bands and how narrow they are.

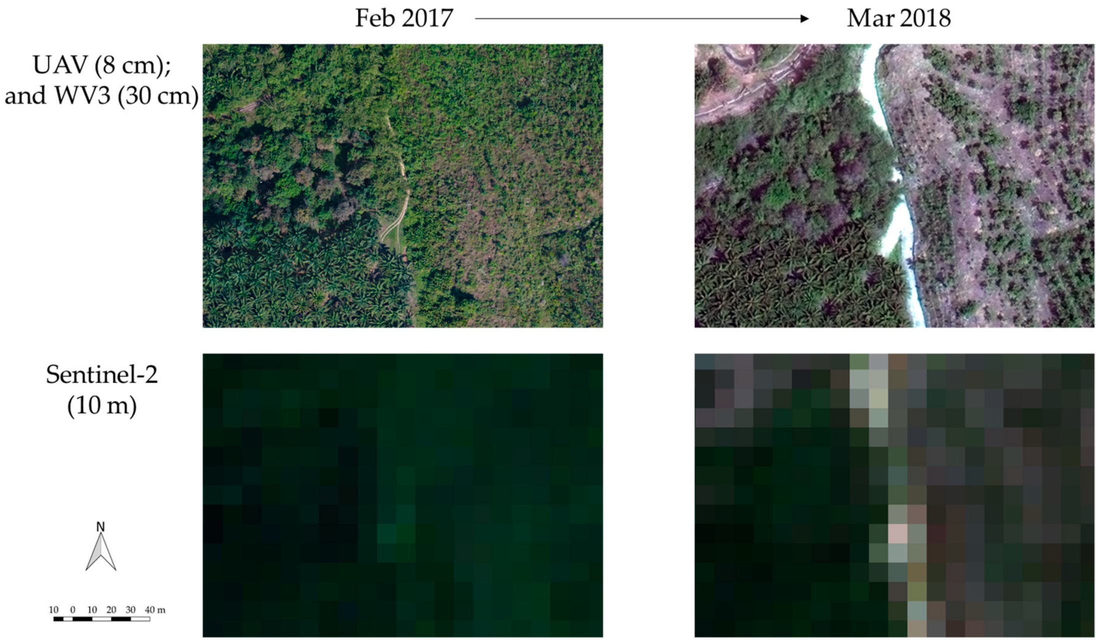


Figure 3.2: Examples of images of the same location using UAV, WV3, and Sentinel-2 in February 2017 and March 2018 (shown in RGB).

Classification methods using machine learning algorithms such as decisions trees, support vector machines, and Random Forests are becoming more popular because of their high accuracy and ability to process complex datasets and produce good results with large numbers of input classification bands and training points (Breiman, 2001; Mountrakis, Im, and Ogole, 2011; Gislason, Benediktsson, and Sveinsson, 2006). Random Forests were selected to classify the S2 data, as it is an algorithm proven to improve the classification accuracy compared to simpler methods, due to its ensemble learning techniques, and it is thus often applied for multispectral and hyperspectral satellite imagery in small areas (Gislason, Benediktsson, and Sveinsson, 2006; Rodriguez-Galiano et al., 2012; Pal, 2005). We also incorporated a texture index in the classification, in order to take advantage of the 10 m information in some S2 bands (even though we performed the classification at 20 m, the resolution of most S2 bands), as local texture is known to increase accuracy (Feng, Liu, and Gong, 2015; Laliberte and Rango, 2009).

Mapping using complex machine learning classifier models and many classifier layers requires a large amount of representative datasets to train the classifier while avoiding over-fitting (Lu and Weng, 2007; Maxwell, Warner, and Fang, 2018). Therefore, the quality and quantity of training samples affect the classification results (Lu and Weng, 2007; Maxwell, Warner, and Fang, 2018; Lu et al., 2004). Such samples can be collected from the field or high resolution images, which allows users to see individual trees (Maxwell, Warner, and Fang, 2018; Foody et al., 2006). We used high resolution images from UAV and WorldView-3 to manually delineate reference data through object recognition, producing a dataset with similar characteristics to ground truth points collected in the field, but at a much lower financial and time cost per point.

In summary, the study aimed to answer the following questions: (1) how accurately we can map areas with small plantations with S2 using a Random Forest classifier; and (2) are such maps accurate and consistent enough that they could be used to confidently detect area changes over a 12-month period? Using our sites in Southern Myanmar as a case study, we are proposing a cost-effective, simple, and transparent approach for mapping small plantations in increasingly common and complex landscapes, which can be applied in other parts of Asia and Africa, where this type of landscape and rapid landcover change are prevalent.

3.2 Materials and Methods

3.2.1 Study Site

We conducted our analysis in two areas, totaling 13,330 ha, containing oil palm (*Elaeis guineensis*) plantations in the Dawei district, Tanintharyi region, Myanmar (Figure 3.3). The Tanintharyi region is in southern Myanmar and west of Thailand, where the development of oil palm plantations started in 1999. Among three districts in the region, Dawei is located to the north, and in general, has older oil palm plantations than those areas to the south. Oil palm companies in this area are believed to be less active, as the dryer climate creates less favourable conditions for oil palm plantations, compared to the other two districts in the south (Baskett, 2016). However, it has been reported that a conflict between villagers and one oil palm company in Area B resulted in a lawsuit in 2016, indicating that there are some actively managed plantations in the area (Su Phyo Win, 2016).

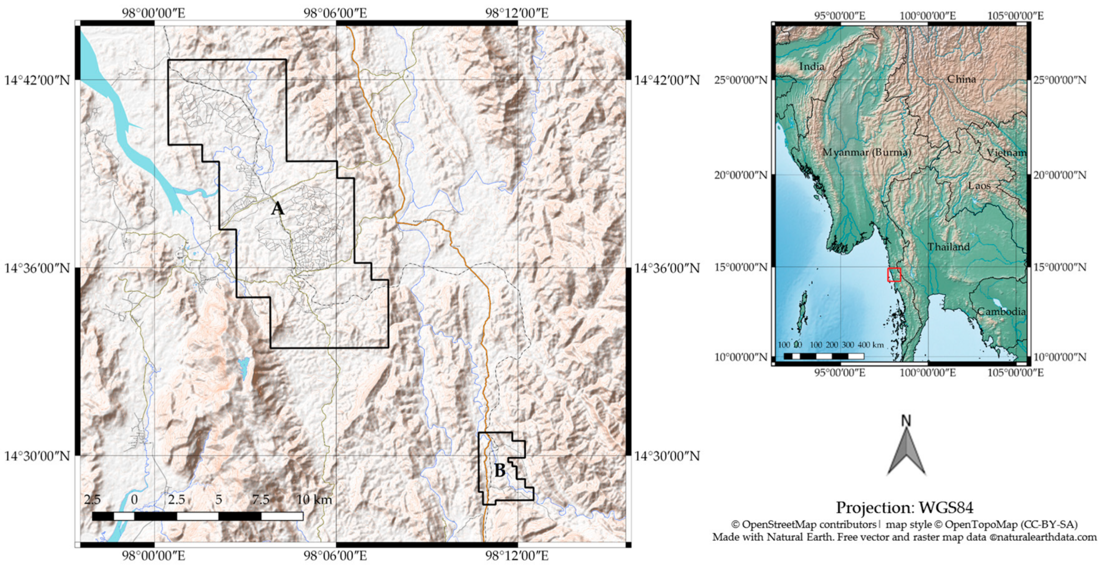


Figure 3.3: Study sites (A and B) covering oil palm plantations in Dawei district, Tanintharyi, Myanmar. The maps were created with OpenStreetMap contributors (left) and Natural Earth (right).

There are two other types of tree crops grown to a significant extent in the area: rubber (*Hevea brasiliensis*) and betel nut (*Areca catechu*) plantations. Fortunately all three are planted in different ways and have characteristic shapes, making it possible to distinguish them using hyperspatial remote sensing. Rubber plantations tend to be polygonal in shape with semi-circular portions and each plantation is smaller than an oil palm plantation. At the same time, rubber plantation areas can be large as often there are many plantations established next to each other (Figure 3.4a), whereas oil palms are typically planted in one large area (Figure 3.4b). Furthermore, rubber plants tend to be planted in straight lines, while oil palm trees are planted in a triangular form using a 9 m distance between trees. Betel nut trees are slender palm trees with numerous linear leaflets (Figure 3.4c) (Lim, 2012). Betel nut plantations are much smaller than the other two crops, and are normally planted in small patches, often abutting or among the other tree crops, along the roads, or between houses. While there are these crop specific plantation styles, they are also seen planted next to each other or in close proximity (Figure 3.4d).

3.2.2 Dataset

Sentinel-2 Images for Classification

Sentinel-2 images for the two areas were obtained in Google Earth Engine as image collections within the months of February 2017, and February and March 2018, corresponding to the months when UAV and WV3 images were collected in each area (Table 3.1). Google Earth Engine allows users to create a single-value composite from a stack of all images collected (an image collection) by selecting the median value of each band for each pixel in the collection. Using images of less than a 10% cloudy pixel to build up the collection ensured that the median composites were cloud free over the set time periods. This was possible because most of the areas had clear images during the study periods. However, a composite for Area A in February 2017 contained clouds in the site when using median values, thus the least cloudy image was used instead of the median values of the images. The code used to process and classify S2 images is available in Supplementary materials.

While certain spectral bands will inevitably be more important than others for the classification, in general, it has been shown that the more spectral bands are included, the better the accuracy, until a certain threshold is reached; following this, the accuracy becomes established (Lee, Skutsch, and Sandker, 2018; Pal and

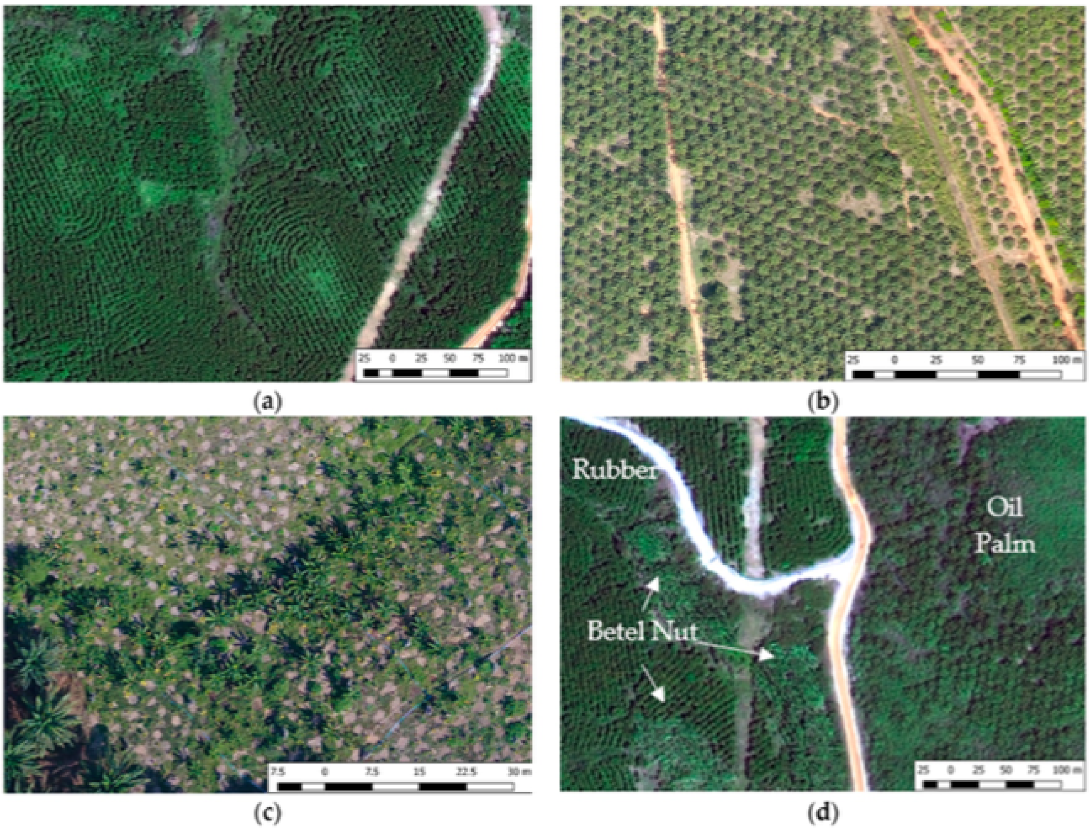


Figure 3.4: High resolution imagery of the study sites showing (a) rubber plantations (WV3); (b) oil palm plantation (UAV); (c) betel nut trees in comparison to oil palm trees on the lower left (UAV); (d) all three crops (WV3). UAV images were provided by the Centre for Development and Environment (CDE) — OneMap Myanmar, Yangon, Myanmar; WorldView-3 imagery © 2018 DigitalGlobe, Inc. — provided by European Space Imaging. North is at the top of each image in the figure. See Supplementary Information for these images in Sentinel-2 RGB.

Area	Month Year	Tile	Cloudy Pixel %	Granule ID
A	Feburary 2017	47PLS	0	$L1C\_T47PLS\_A008681\_20170219T035623$
	February 2018	47PLS	9.7756	$L1C\_T47PLS\_A013829_20180214T040242$
		47PLS	0	$L1C\_T47PLS\_A004992\_20180219T034801$
		47PMS	0.6386	$L1C\_T47PMS\_A004992\_20180219T034801$
		47PLS	1.8035	$L1C\_T47PLS\_A013972\_20180224T040129$
B	February 2017	47PMS	0.3121	$L1C\_T47PMS\_A008538\_20170209T035553$
		47PMS	0	$L1C\_T47PMS\_A008681\_20170219T035623$
	March 2018	47PMS	0.2107	$L1C\_T47PMS\_A005135\_20180301T035914$
		47PMS	0	$L1C\_T47PMS\_A014115\_20180306T035825$
		47PMS	0.0943	$L1C\_T47PMS\_A014258_20180316T034812$
		47PMS	0.0604	$L1C\_T47PMS\_A005421_20180321T040215$

Table 3.1: Sentinel-2 images used for classification.

Mather, 2006; Sarmah and Kalita, 2016; Thenkabail et al., 2004; Lerma, 2001; De Backer et al., 2005; Dalponte et al., 2009; Le Bris et al., 2016). Therefore, all of the spectral bands in the Sentinel-2 images were selected to train the classifier (Table 3.2). In addition, two indices were included: the normalised difference vegetation index (NDVI; Equation (3.1)) (Tucker, 1979) to give the greenness of vegetation; and the standard deviation of NDVI (moving window square 5 $\times$ 5 kernel), both calculated at a 10 m resolution. The standard deviation of NDVI gives the texture of greenness, which is commonly used for object-based classification using high resolution images (Feng, Liu, and Gong, 2015; Laliberte and Rango, 2009). After adding the spectral bands, NDVI, and texture index, the images were scaled to a 20 m spatial resolution.

$$NDVI = \frac{(B8 - B4)}{(B8 + B4)} \tag{3.1}$$

where NIR is B8 and RED is B4.

Name	Resolution	Wavelength	Description
B1	60 m	443.9 nm (S2A)/442.3 nm (S2B)	Aerosols
B2	10 m	496.6 nm (S2A)/492.1 nm (S2B)	Blue
B3	10 m	560 nm (S2A)/559 nm (S2B)	Green
B4	10 m	664.5 nm (S2A)/665 nm (S2B)	Red
B5	20 m	703.9 nm (S2A)/703.8 nm (S2B)	Red Edge 1
B6	20 m	740.2 nm (S2A)/739.1 nm (S2B)	Red Edge 2
B7	20 m	782.5 nm (S2A)/779.7 nm (S2B)	Red Edge 3
B8	10 m	835.1 nm (S2A)/833 nm (S2B)	NIR
B8a	20 m	864.8 nm (S2A)/864 nm (S2B)	Red Edge 4
B9	60 m	945 nm (S2A)/943.2 nm (S2B)	Water vapor
B10	60 m	1373.5 nm (S2A)/1376.9 nm (S2B)	Cirrus
B11	20 m	1613.7 nm (S2A)/1610.4 nm (S2B)	SWIR 1
B12	20 m	2202.4 nm (S2A)/2185.7 nm (S2B)	SWIR 2

Table 3.2: Spectral bands in Sentinel-2.

Reference Data Points from UAV and WorldView-3

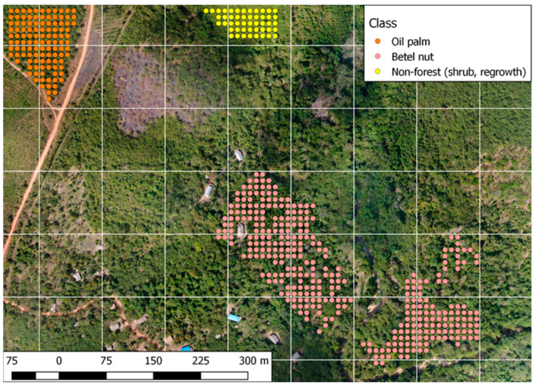
We obtained high resolution images of two areas (12,306 ha and 1024 ha) surrounding oil palm plantations in the Dawei district, Tanintharyi region, Myanmar (Figure 3.3) (Centre for Development and Environment, 2018; Imaging, 2018). The images were collected on 8 and 9 February 2017 by unmanned aerial vehicles (UAV) and on 12 February and 3 March 2018 by WorldView-3 (WV3) in Area A and B, respectively. The UAV images are at approximately an 8 cm spatial resolution and have three spectral bands (red, green, blue), while WV3 images are provided at a 30 cm resolution with four spectral bands, including red, green, and blue, as well as a near infrared (NIR) band (Table 3.2). The WV3 data is a geometrically- and terrain-corrected pan-sharpened product provided by DigitalGlobe, using the 31 cm resolution panchromatic band to increase the resolution of four of the 1.24 m resolution multispectral bands (RGB and near infrared). The UAV images were processed and mosaicked with Agisoft Photoscan (Centre for Development and Environment, 2018). Both images were georeferenced to the S2 images using the Georeferencer GDAL plug-in on QGIS.

Sensor	Area	Camera / Sensor	Spatial Resolution	Spectral Bands	Date Acquired
UAV	A	Phantom 4 Professional built-in camera (20MP, FOV 84°)	8 cm	3 (RGB)	8 February 2017
	B				9 February 2017
WV3	A	WorldView-3 (4-band pan-sharpened multispectral product)	30 cm (as provided)	4 (RGB, NIR)	12 February 2018
	B				3 March 2018

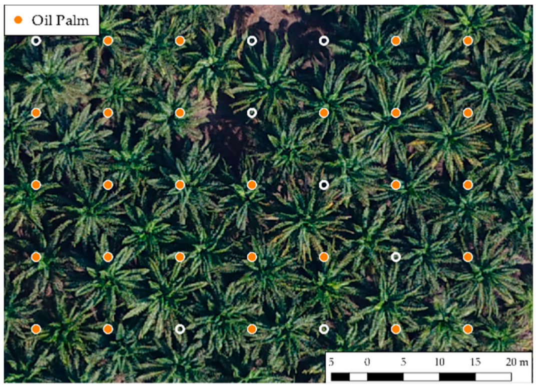
Table 3.3: Technical specifications of the sensors used in the study and image acquisition dates.

Reference data for training and validation were collected from these images where there were no visible changes in the land cover between the two periods, and where clear images were available. The data were collected according to seven classes of land cover: oil palm, rubber, betel nut, forests (non-plantation, dense tree cover), non-forest (shrubs, regrowth, and other vegetation), bare land, and water. Various plantations in the region were visited from 5 to 25 March 2017 in order to understand the land cover types.

The dot grid photointerpretation method was used in collecting reference data from the hyperspatial imagery (Figure 3.5) (Lister, Lister, and Doyle, 2009; Nowak et al., 1996). The dot grid method is a traditional approach used by foresters for area estimation (Barrett and Philbrook, 1970; Bonnor, 1975). We preferred this method over delineating polygons manually because of its systematic nature, lack of subjectivity, and the speed of collecting samples. The dots were systematically superimposed over the images at 10 m intervals. If the dot fell on a certain class, it was collected as reference data of that class (Figure 3.5a). In the case of oil palm trees, the dot could fall between palm leaflets; in this case, we included that dot as reference data for the oil palm if the dot fell between the leaflets but within the circle connecting the edges of the palm fronds (Figure 3.5b). Since the classification was performed at 20 m, we avoided collecting samples of different classes that were too close to each other, in order to avoid mixed samples within 20x20.



(a)



(b)

Figure 3.5: Dot-grid photointerpretation method showing an example of reference data collected for (a) oil palm, betel nut, and shrub (UAV, Area A, 2017); (b) oil palm trees were identified with orange dots if they fell within the circle of palm canopy (UAV, Area B, 2017).

The method to split reference data into training and testing data or use a subset of training data for cross-validation ("holdout" or "Out of the Box Testing") is a common approach in supervised classification using machine learning algorithms (Foody, 2017; Fardanesh and Ersoy, 1998; Prechelt, 1998; Huynh and Setiono, 2005). We therefore took such an approach in our study, randomly assigning pixels within our dataset to 'test' or 'training' datasets.

However, depending on how training and testing are sampled, there is a risk of auto-correlation and thus over-estimation of the true map accuracy (Foody, 2017; Millard and Richardson, 2015; Twomey and Smith, 1998). Our approach, randomly selecting pixels from within the same polygons and assigning them to test or training sets, is prone to this criticism. Furthermore, our active selection of training and test datasets only from areas where from field knowledge and the presence of high resolution remote sensing data we had high confidence in that particular land cover, also has a tendency to inflate accuracy. These problems have been faced by other studies mapping land cover, who have used similar methods as ours (e.g. Draper et al., 2014; Yu et al., 2016; Cheng et al., 2016; Margono et al., 2014; Immitzer, Vuolo, and Atzberger, 2016). We chose to do this however because alternative approaches had significant issues:

1. Finding training areas where we were confident, and pixels were a certain, unmixed class was very challenging in our study sites, due to its complex landscapes. Assigning a random pixel across the image to a particular class with confidence was highly unlikely, meaning a test dataset designed such a way would have contained unreliable data.

2. Choosing a random set of our training polygons, rather than pixels within those polygons as test data, would have involved removing key training sites, resulting in withholding necessary information for a classifier to produce a more accurate map.

In order to produce robust results, we collected a large amount of reference data (Table 3.4) and conducted 1,000 iterations with different random seeds for training and testing datasets (see the next section).

Area	Forest	Oil Palm	Rubber	Betel Nut	Non-Forest[1]	Bare Land	Water	Total
A	2,228	4,216	3,191	915	4,881	1,667	303	17,401
B	1,588	988	1,577	681	1,257	1,346	194	7,631
Total	3,816	5,204	4,768	1,596	6,141	3,013	497	25,032

Table 3.4: Reference data collected for training and validation. [1]Shrub, regrowth, other plantations.

In total, 25,032 reference points (number of dots, placed at 10 m intervals) were collected, among which 50% of the points in each class were randomly selected for training, and the other for accuracy assessment (Table 3.4). A large number of training points is required when using a machine learning algorithm and a many band multi-spectral image (Rodriguez-Galiano et al., 2012; Maxwell, Warner, and Fang, 2018; Lu et al., 2004; Chen and Stow, 2002). While there is no literature providing the minimum number of training samples for machine learning algorithms, it has been suggested that the number of features (e.g., wavebands) multiplied by 30 can be used as a guidance (Foody et al., 2006). Our samples exceeded this benchmark by 1.5 to 10, except for betel nut plantations in Area B and water class in both areas, which were limited due to the characteristics of the area (limited area of betel nut trees). While there was an attempt to balance the number of points per class, the final set of reference data includes more points for some classes, as it was a result of repeated running of the classifier and the addition of more training data in areas where misclassification was seen to have occurred.

3.2.3 Random Forest Classification Algorithm

The Random Forest classification utilises ensemble methods with multiple tree-type classifiers (Breiman, 2001). Each tree casts a single vote for the most frequent class to the input data by using a randomly generated subset of input variables for that tree (Breiman, 2001; Gislason, Benediktsson, and Sveinsson, 2006; Rodriguez-Galiano et al., 2012; Pal, 2005). Therefore, two parameters for the Random Forest classifier had to be set: the number of classification trees; and the number of prediction variables per node (Table 3.5). As the number of trees increased, the generalization error rate decreased (Breiman, 2001; Rodriguez-Galiano et al., 2012). Based on our experiment and considering the computational burden on Google Earth Engine, we selected 30 trees. The number of prediction variables is used at each node to grow the tree, and is generally set at the square root of input variables for classification models like this (Gislason, Benediktsson, and Sveinsson, 2006; Cutler et al., 2007). Therefore, we set the number of variables as four (the square root of 15). The full Google Earth Engine code used to classify S2 images is available in Supplementary materials.

Random Forest Parameters		Input Variable
Number of trees	Number of prediction variables per node	Number of variables (Spectral bands and indices)
30	4	15 (all B bands, NDVI, texture)

Table 3.5: Summary of parameters and inputs for Random Forest.

In addition, we estimated accuracy rates of the maps and the area change between the two time periods (Olofsson et al., 2013). In order to produce robust classification results for area change, the classification of S2 images was run 1,000 times by randomly selecting 50% of reference data from each class for training, and testing against the other 50% (Dargie et al., 2017). The area of each class produced by each run was used to estimate the confidence intervals for the area change.

3.3 Results

3.3.1 Classification Accuracy

Using the reference samples from high resolution imagery as training data for a Random Forest classifier with 30 trees and four prediction variables, Sentinel-2 data were able to classify both areas at overall accuracy rates of 95% and higher for all the four images[3] (Figure 3.6, Table 3.6). This overall accuracy figure indicates the proportion of the area mapped correctly (Olofsson et al., 2013). Accuracy rates per class were also consistently high across the classes, with more than 84.7% and 93.5% median accuracy rates for user's accuracy (UA) and producer's accuracy (PA), respectively (Table 3.7 and 3.8). UA is the proportion of the area mapped as a particular class that matches with the testing data, while PA

[3]For overall accuracy without texture index, please see the Supplementary Materials.

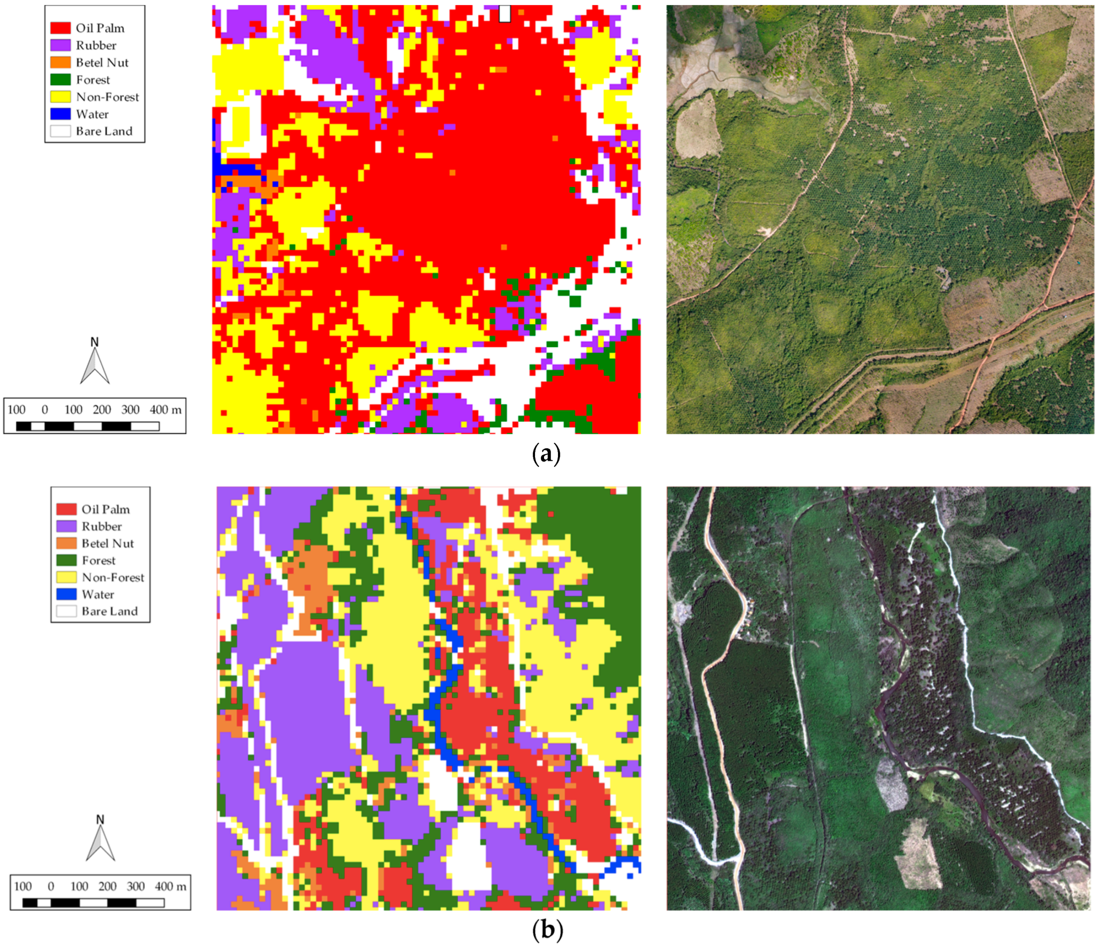


Figure 3.6: S2 classification results for parts of (a) Area A in February 2017 with the UAV image on the right; (b) Area B in March 2018 with the WV3 image on the right.

is the proportion of the area that is a particular class in the testing data and is mapped correctly as that class (Olofsson et al., 2013). Excluding water, the highest average accuracy was 98.4% for rubber (PA), while the lowest average was 84.7% for betel nut (UA).

Area	Month/Year	Median	2.5% Bound	97.5% Bound
A	February 2017	95.9%	95.4%	96.4%
	February 2018	96.0%	95.5%	96.5%
B	February 2017	95.5%	94.5%	96.4%
	March 2018	95.6%	94.6%	96.4%

Table 3.6: Overall classification accuracy using Sentinel-2 data at a 20 m spatial resolution with 1,000 Random Forest classification runs.

Area	Month Year	Oil Palm	Rubber	Betel Nut	Forest	Non-Forest[1]	Bare Land	Water
A	February 2017	95.1%	96.0%	84.7%	96.4%	98.1%	96.1%	97.5%
	February 2018	94.8%	97.1%	86.8%	96.9%	97.8%	96.1%	95.9%
B	February 2017	94.6%	95.2%	93.5%	97.1%	94.8%	97.0%	94.5%
	March 2018	93.5%	96.5%	91.8%	96.9%	97.0%	96.0%	91.9%

Table 3.7: Median user's accuracy per class across the four images. [1]Shrub, regrowth, other plantations.

Although the overall accuracy showed that more than 95% of reference data used for validation was correctly classified, by manually investigating the imagery, we found that some areas we knew to be young rubber plantations were classified as shrubs. Furthermore, the areas with dark shadows of trees, rubber plants,

Area	Month Year	Oil Palm	Rubber	Betel Nut	Forest	Non-Forest[1]	Bare Land	Water
A	February 2017	93.8%	96.6%	97.5%	97.0%	96.1%	96.4%	99.4%
	February 2018	94.8%	98.1%	98.1%	96.9%	96.0%	94.9%	99.3%
B	February 2017	94.6%	94.6%	94.4%	95.6%	95.2%	95.9%	97.7%
	March 2018	93.%	98.4%	94.1%	94.5%	94.0%	96.9%	94.0%

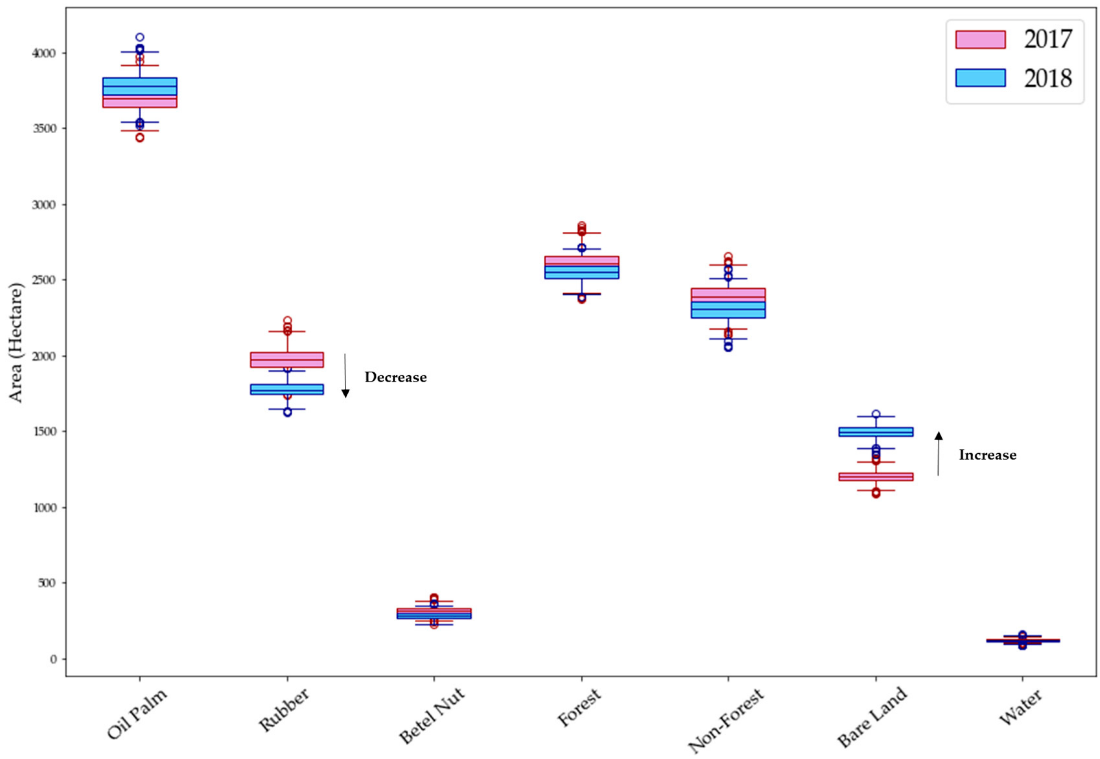
Table 3.8: Median producer's accuracy per class across the four images. [1]Shrub, regrowth, other plantations.

or shrubs were sometimes classified as oil palm, along with the edges of rubber plantations or shrubs. Conversely, some oil palm plantations with less shadow contrast (e.g., oil palm plantations that have been poorly weeded and contain shrubs between the trees) were classified as rubber or shrubs. These misclassifications tend to occur more in the larger area (Area A) and also in the area further from the closest reference data.

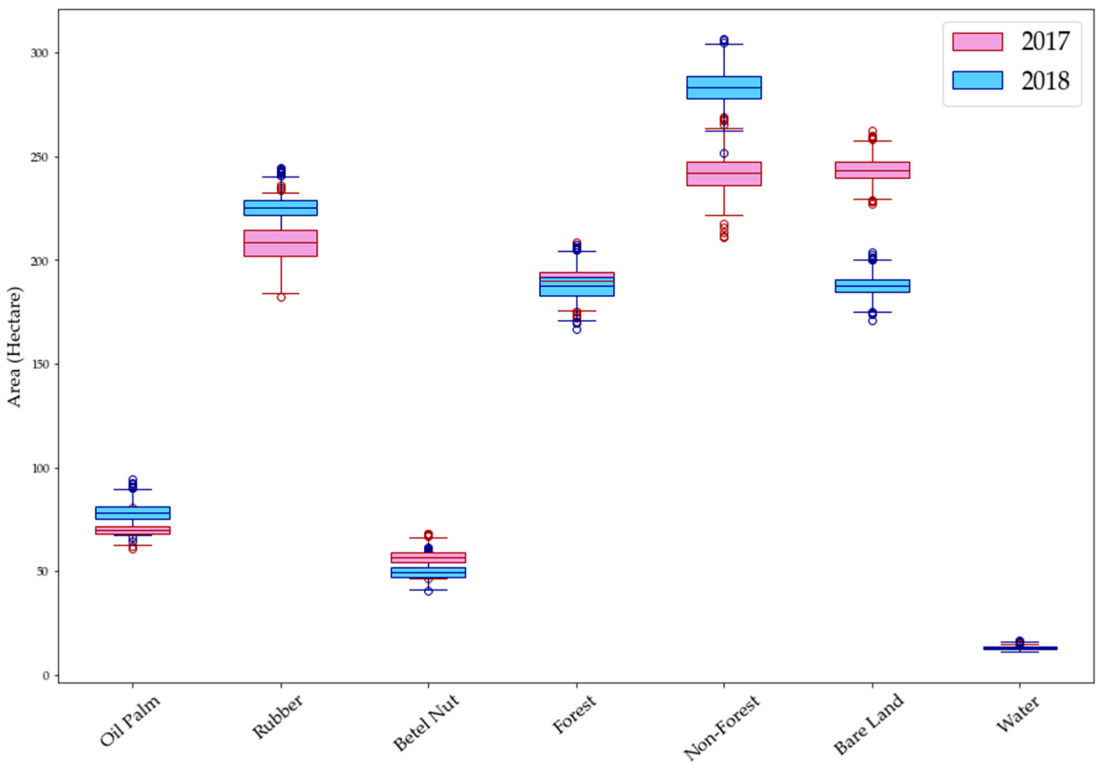
3.3.2 Area Change with Sentinel-2

The area changes from 2017 to 2018 were examined by considering the differences between the years, compared to the spread of values from the 1,000 iterations. Figure 3.7 shows boxplots for each area in 2017 and 2018: the median value of the area size (hectare) of each class, the minimum and maximum values, and the 25th and 75th percentiles indicating 50% of the distribution of the data. We considered it likely that there was a significant change if there was no overlap in the interquartile ranges of the two sets of data (represented graphically as no overlap in the box portion of the boxplots in Figure 3.7). In Area A, the changes were significant for three classes: rubber, betel nut, and bare land. In Area B, most of the classes show differences in area, except for forest and water classes (Figure 3.7).

Taking the median values of the results, in Area A, bare land increased by 24%. This indicates the clearing of trees between 2017 and 2018, which seems to be



(**a**)



(**b**)

Figure 3.7: Classification results: area changes by class in (a) Area A; (b) Area B, showing the spread of area values from the 1,000 iterations of the classification using different random subsets of the training dataset.

accompanied by decreases in betel nut and shrub areas. The rubber plantations also showed a decline of 10%; however, the visual interpretation shows a clear increase of rubber, especially in the south of Area A. This may be due to an overestimation of rubber plantations in 2017, as most of the rubber plantations were young, making them difficult to distinguish from other classes, especially shrubs, resulting in more pixels classified as rubber sporadically across the area, as well as around the edges of various vegetation types.

In Area B, shrub area and oil palm plantations increased by 17% and 11%, respectively. It should be noted that increases in plantations do not indicate planting of the crop between 2017 and 2018, as such new plantations are more likely to be classified as bare land or shrubs. Rather, the increases show the growth of crops that were planted a few years earlier, to the point where they become detectable. The rubber plantations also show an increase of 8%. Similarly to Area A, most of the rubber plantations were young in 2017, and the classified map shows a widespread increase of rubber in 2018. These increases in plantations and shrubs are consistent with a decrease in bare land.

3.4 Discussion

The main advantage of Sentinel-2 (S2) data is its multispectral instruments with 13 bands, which we believe was the main factor in achieving high accuracy rates (Supplementary Figure B.1). Therefore, for the purpose of classification, it is not necessary to have a spatial resolution sufficient to see individual trees in order to differentiate tree crops. In fact, the level of accuracy achieved in this study (>95%) is higher than the average accuracy rates achieved with hyperspatial images with object-based classification methods (Feng, Liu, and Gong, 2015; Amini et al., 2018; Ma et al., 2017).

The high spatial resolution of S2, at 10 to 20 m, should be sufficient to classify even very small plantations, making it the ideal tool for mapping fragmented landscapes. While this study used the 20 m spatial resolution for classification, using lower spatial resolutions will likely achieve an even higher accuracy, depending on the purpose of classification and the type (and size distributions) of plantations in the area. In addition, more texture indices may improve the performance of the classifier.

A close examination of the maps, however, revealed limitations of classification accuracy when classifying a large area. The difficulty in classifying the area without reference data nearby implies that more reference data are necessary. However, adding more data will be limited, depending on the computation capacity of the program used. Therefore, the target area has to be limited to a certain extent, considering the computational burden, time, and labour, when classifying complex landscapes.

Furthermore, the levels of maturity or growth of plantations in the reference data affect the ability of the classifier, as evidenced by the impacts of young rubber plantations in 2017. As young plantations tend to confuse the classifier, it is recommended that the year or area where sufficient reference data with mature plantations are available is selected, and it should be accepted that plantations of particular species will only become visible in the classification after a few years of growth. While it is possible to classify crops like betel nut plantations that exist in small patches made of small trees, it remains as a challenge to classify young plantations themselves.

It is also important to note that the results are sensitive to each and every reference data point, which are entirely based on the judgement and skill of the interpreter. In addition to a priori knowledge of the area, precision and meticulousness in selecting reference data is required, especially when classifying complex landscapes at a high resolution. In this study, reference data were selected from where the interpreter can be certain about the class based on the images and knowledge of the area. Therefore, by excluding the areas with possibly mixed classes where they are difficult to classify, the reported accuracy may be higher than reality. This could be fixed by creating a test dataset from random, rather than a selection of ‘ideal’, points. However, the difficulty here is that error would then exist in the test dataset, confusing the interpretation of results.

3.5 Conclusions

Sentinel-2 (S2) data can successfully classify complex landscapes with small plantations, forests, and shrubs with more than a 95% overall accuracy against independent test data. While different trees crops are not visibly distinguishable in S2 images, when trained with reference data, S2 can classify small plantations such as rubber and betel nut trees with more than a 94% and 85% accuracy, respectively. However, quantifying the changes between 2017 and 2018 presented a challenge due to the dominance of young rubber plantations in 2017 in these particular study areas. The interpretation of the results is therefore limited to: the increase of bare land in Area A, due to the clearing of betel and rubber trees; and the decrease of bare land in Area B due to the increase of shrubs, oil palm, and rubber plantations, which are likely to have been planted a few years earlier. The results show a contrast in the level of activities in tree clearing and the trend of rubber plantations in two areas.

The accuracy results indicate the strength of Sentinel-2’s multispectral bands in producing accurate classifications of similar land cover classes at a high (20 m) resolution. However, it should be noted that a large amount of reference data is required to classify complex landscapes with confidence, which restricts the size of the area to be classified, given limitations in terms of the collection of training points and the analysis of data.

3.6 Acknowledgements

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Chapter 4

Oil palm concessions in southern Myanmar consist mostly of unconverted forest

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Abstract

The increased demand for palm oil has led to an expansion of oil palm concessions in the tropics, and the clearing of abundant forest as a result. However, concessions are typically incompletely planted to varying degrees, leaving much land unused. The remaining forests within such concessions are at high risk of deforestation, as there are normally no legal hurdles to their clearance, therefore making them excellent targets for conservation. We investigated the location of oil palm plantations and the other major crop – rubber plantations in southern Myanmar, and compared them to concession boundaries. Our results show that rubber plantations cover much larger areas than oil palm in the region, indicating that rubber is the region's preferred crop. Furthermore, only 15% of the total concession area is currently planted with oil palm (49,000 ha), while 25,000 ha is planted outside concession boundaries. While this may in part be due to uncertain and/or changing boundaries, this leaves most of the concession area available for other land uses, including forest conservation and communities' livelihood needs. Reconsidering the remaining concession areas can also significantly reduce future emission risks from the region.

4.1 Introduction

Oil palm (*Elaeis guineensis Jacq.*) plantations have increased in area from 3.2 million ha in 1970 to 21 million ha in 2017 (FAO, 2019). Most of the land for these plantations has come from the clearance of tropical forest, thereby contributing large CO_2 emissions to the atmosphere, and thus intensifying climate change (Gibbs et al., 2010; Gaveau et al., 2016; Abood et al., 2015; Vijay et al., 2016; Koh and Wilcove, 2008). The clearance of forest, along with this climate change, will together have further detrimental impacts on biodiversity and cause a reduction in the provision of ecosystem services (Vijay et al., 2016; Koh and Wilcove, 2008; Gaveau et al., 2014). Oil palm has also transformed livelihoods across the tropics, especially in Southeast Asia, where it has become the main export crop from countries such as Indonesia and Malaysia (FAO, 2019; Sayer et al., 2012). One can easily comprehend why: oil palm is exceptionally productive in optimal conditions, producing five times more oil per hectare than any other oil crop (Woittiez et al., 2017; Lam et al., 2009). The resulting low price has created an increasing global demand, and the use of palm oil has expanded beyond food and personal care products to biofuel (Henson, 2012; Gerasimchuk and Koh, 2013). However, much of the area where oil palm now grows were until recently forests: an estimated 45% of oil palm in Southeast Asia grows on land that was forest in 1989 (Vijay et al., 2016). In Kalimantan, Indonesia, 47% of lands converted to oil palm from 1990 to 2010 were previously intact forests (Carlson et al., 2013). There exists some pressure to increase the sustainability of palm oil by reducing deforestation, which has led to the establishment of certification schemes. However, the continued growth in palm oil production is also driven by demand from developing economies, where price sensitivity trumps sustainability (Schleifer and Sun, 2018).

Although the relationship between the expansion of oil palm plantations and declining forest area is well established (Gibbs et al., 2010; Abood et al., 2015; Vijay et al., 2016; Koh and Wilcove, 2008; Gunarso et al., 2013), the proportion of unplanted areas within oil palm concessions is not well known. According to the report "Hidden Lands, Hidden Risks?" by the Zoologist Society of London (Zoological Society of London, 2017), out of 8.6 million ha of land assigned for oil palm plantations (reported by the 50 largest oil palm companies), 1.4 million ha were of unclear use or still remain unplanted. Meanwhile, 35 companies did not report unplanted areas. Other regional figures suggest this may be the tip of the iceberg: one study found that there may be as much as 1.7 million ha of standing forests in oil palm concessions in Indonesia alone (Abood et al., 2015). If cleared, this would amount to emissions between 356-639 Tg C (Abood et al., 2015). Another study found that that approximately 79% of oil palm concessions in Kalimantan, Indonesia have still not been planted (Carlson et al., 2013). If planted, 9 million ha of tropical forests (41% of intact forests) will be converted, resulting in 3.6-4.5 Pg C (Carlson et al., 2013).

The potential for conservation to change the fate of these as-yet-unconverted forests is significant. While there are typically lags between the time when the concession is granted and clearing the land and planting the crop is started, this cannot account for the degree of unplanting observed. Clearly, the development of oil palm is influenced by market conditions and the political environment, both at a national and local scale (Gaveau et al., 2016; Carlson et al., 2012). Further, some concession areas present high social andor environmental risks and therefore remain unexploited (Zoological Society of London, 2017). For example, in Myanmar, the location of this study, there are conflicts over land ownership and access in some concession areas that are controlled by an insurgent group or occupied by wildlife (e.g. elephants) (Baskett, 2016; Woods, 2015; Eames et al., 2005). The conflict also involves communities that returned to the region after the ceasefire agreement was signed in 2012, where the area has since been allocated for oil palm (Woods, 2015; "After decades of conflict, land deadline looms for Myanmar villagers" 2019). In addition, many concessions include lands that are simply unsuitable for plantations (e.g. steep slopes, lack of infrastructure for access) (Baskett, 2016). Furthermore, many of the companies who hold concessions lack the resources, knowledge or even interests in investing in oil palm plantations (Baskett, 2016; Woods, 2015). While they engaged in logging where accessible, planting did not follow and large areas of concessions remain unused (Baskett, 2016; Woods, 2015). For the last few years, the government has been conducting oil palm land use assessment with the aim of allocating unused land to communities (Su Phyo Win, 2016).

Myanmar presents significant opportunities for conservation and sustainable development within oil palm concession areas. Although Indonesia is the largest oil palm producer today, its climate suitability for Palm Oil is projected to decrease significantly by 2050, while the climate suitability is projected to increase in Myanmar (Paterson et al., 2017). There are approximately 2 million ha of intact forests (estimates ranging from 1.9 million ha in 2016 and 2.3 million ha in 2014) in Southern Myanmar where oil palm concessions have been granted (Connette et al., 2016; Bhagwat et al., 2017). One reason for this is that prior to 1999, Myanmar had little history of oil palm industry development. Oil palm was introduced to the country in the 1920s (Ministry of Agriculture, Livestock and Irrigation, 2014). Thereafter and from the 1970s on, oil palm plantations were developed in Tanintharyi, Mon, Kachin, Rakhine states (Ministry of Agriculture, Livestock and Irrigation, 2014). Yet, large scale development of oil palm plantations was only initiated in 1999, when it became a focus of the Myanmar government, with efforts concentrated in the southernmost part of the country: the Tanintharyi region, where the conditions were considered particularly favourable (Figure 4.1) (Baskett, 2016; Saxon and Sheppard, 2014). To meet domestic demand, and with the aim of going into an export industry, the government set a target of planting 202,343 ha by 2030 (500,000 ac, later increased to 700,000 ac (283,280 ha)), including about 63,000 ha of reserved forests) (Baskett, 2016; Eames et al., 2005). Under the then military regime, selected companies were tasked to operationalise the cultivation of oil palm. Since then, 401,814 ha of oil palm concessions have been allocated to 44 companies (Figure 4.1), including some concessions overlapping with proposed national parks (Baskett, 2016). Of these, approximately 35% of the total concession areas (140,247 ha) are reported to have been planted (as of 2015) (Baskett, 2016). In Tanintharyi, the deforestation between 2001 and 2010 amounted to an estimated 164,200 ha (Wang and Myint, 2016). The decline of forest extent was particularly high in one of the proposed national parks (Lenya) (98.0% to 95.2% between 2002 and 2016) (Connette et al., 2017).

It is worth noting that oil palm is not the only major commodity crop in the region (Thein et al., 2019). Tanintharyi also has large areas of rubber plantations, with their total extent the second largest of any region of the country (Kenney-Lazar, 2016). Although concession data are not available as rubber plantations include smallholders, planted areas increased from 82,047 ha in 2008-2009 to 138,828 ha in 2015-2016, likely due to market liberalisations and an increase in the rubber price over the last two decades (Woods, 2015; Kenney-Lazar, 2016; Isabelle Vagneron et al., 2017).

Our study therefore investigates the current extent of oil palm and rubber plantations in Tanintharyi, Myanmar, and compares them to concessions and other boundaries. We estimated the area of oil palm as well as other land cover classes by conducting a machine learning classification on Sentinel-1 and Sentinel-2 satellite data from 2018-2019 using thousands of reference data points. Sentinel data are provided at a high resolution (10m for Sentinel-1 and 10-60m for Sentinel-2) with very narrow bands that enable some differentiation of spectral responses from vegetation that was previously only possible using hyperspectral sensors (Sentinel-2's B5-7, 8A), which is necessary to classify the region with complex landscapes with small patches of plantations and forests (Nomura and Mitchard, 2018). Furthermore, their frequent revisits (6/12-day for Sentinel-1, 5-day for Sentinel-2) made it possible to create a high-quality composite based on the average of many scenes, reducing radar speckle (S1) and sun-angle and seasonal

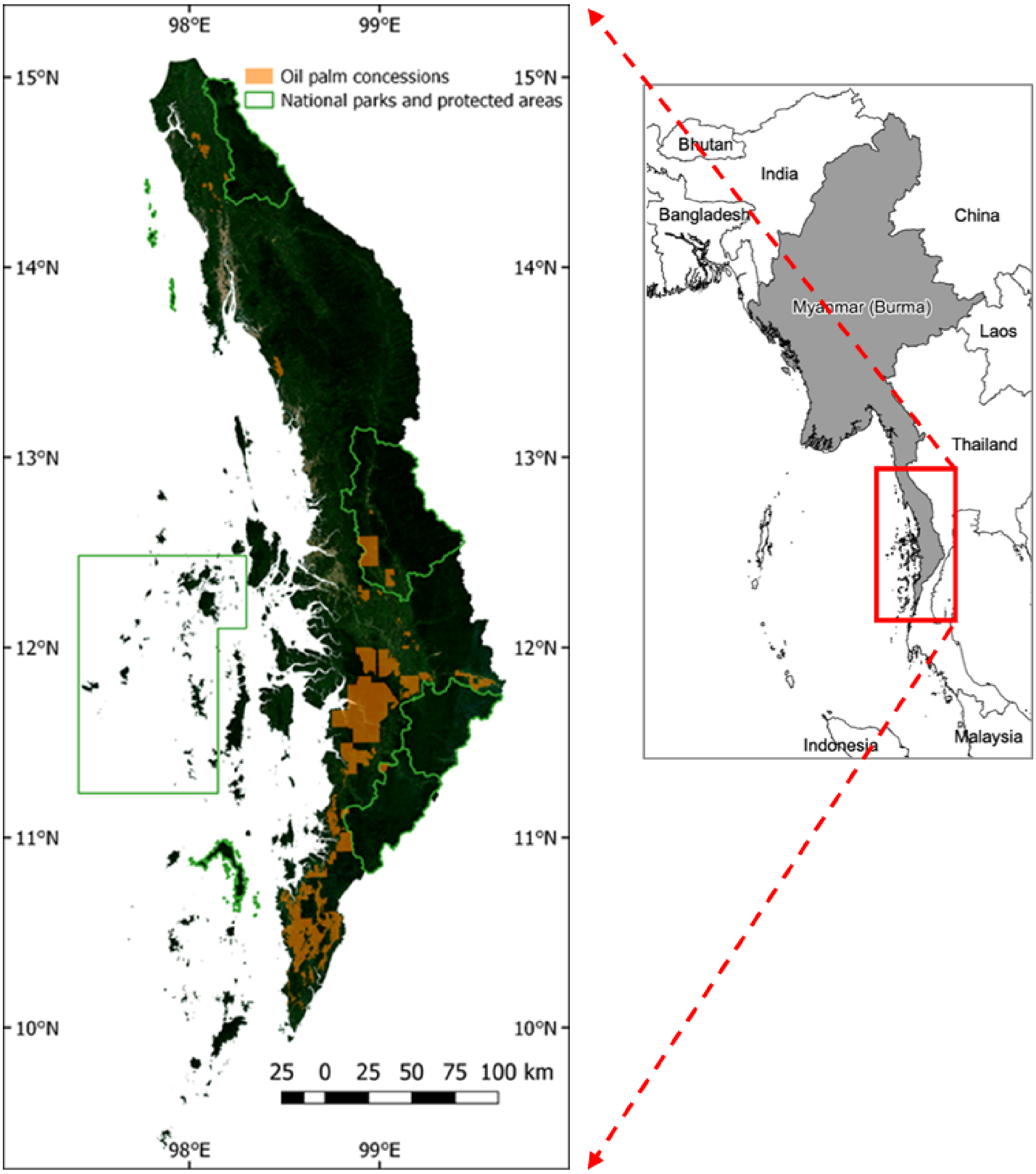

Figure 4.1: Tanintharyi region in Myanmar, Southeast Asia (right); oil palm concessions, national parks (designated and proposed), protected areas in the region (left) as of 2018. Note that approximately 25,000 ha of concession area overlap with two proposed national parks (the Tanintharyi National Park and the Lenya National Park). The underlying map on the left is the Sentinel-2 cloud-free composites between November 2018 and January 2019.

effects (S2). The classification consists of six classes: mature oil palm, mature rubber trees, other trees, shrub, bare land, and water. By understanding the scale of oil palm plantations in Myanmar and identifying the total unplanted areas within concessions, our study provides critical information on the suitability and availability of land without the two crops that could be reassigned for other land use, including for communities to meet their livelihood needs and conservation of remaining forests. The impacts also transcend those related to forest cover and carbon: the area includes wildlife sanctuaries, national parks and other protected areas and is listed as a biodiversity hotspot. It hosts Sundaic flora, fauna as well as endemic and endangered species such as the Gurney's Pitta (*Pitta gurneyi*), the Sunda pangolin (*Manis javanica*), and two recently discovered species of bent-toed geckos (*genus Cyrtodactylus*) (Eames et al., 2005; Connette et al., 2017; Aung et al., 2017).

4.2 Methods

4.2.1 Data

Optical, radar, and elevation data were used to classify the Tanintharyi region into six classes: oil palm, rubber, shrub, other trees, bare land, and water, using Google Earth Engine. Sentinel-2 (S2) data (optical) were obtained as image collections for the period between 01/11/2018 and 31/01/2019 (Table 4.1). Cloudy pixels were processed using the cloud mask (QA60 band) provided in S2 data as well as a set of algorithms built to detect clouds using relevant B bands (B1, B2, B8, B10 and B11). These algorithms were customised for the region to create cloud-free image composites (See *Supplementary materials*). The final image was produced by computing the mean of all bands in the 40 to 60 percentile range, and 10 bands (B2-B8A, B11-B12, all 10 or 20 m resolution) were selected for classification. In addition, two indices were included to detect vegetation through the greenness and texture: the normalised difference vegetation index (NDVI; Equation below);

Data	Period	Bands	Number of images
Sentinel-2 MSI: MultiSpectral Instrument, Level-1C	November 2018 to January 2019	B1-B12 [B1 and B10 were used for cloud detection only]	482
Sentinel-1 SAR GRD: C-band Synthetic Aperture Radar Ground Range Detected, log scaling	January 2018 to January 2019*	VV, VH	404

Table 4.1: Sentinel-2 and Sentinel-1 data used for classification. *January 2018 to March 2018 are from the ascending angle only; the remainder of the period are from both descending and ascending angles. Sentinel-1 images had already been pre-processed in Earth Engine with Sentinel-1 Toolbox, including: thermal noise removal; radiometric calibration; and terrain correction using SRTM 30 or ASTER DEM for areas greater than 60 degrees latitude, where SRTM is not available.

and the standard deviation of NDVI (moving window 5x5 pixels), both calculated at a 10 m resolution (Tucker, 1979). NDVI was selected over other indices (e.g. EVI, LSWI, SATVI) based on our previous study, which successfully classified similar landscapes in this region with high accuracy (Nomura and Mitchard, 2018). Including other indices did not result in significant changes in accuracy for our study. Furthermore, we avoided using closely correlated bands together in classifications as they can increase the chances of overfitting, and increase computation time, without increasing accuracy (De Backer et al., 2005; Dalponte et al., 2009).

$$NDVI = \frac{(B8 - B4)}{(B8 + B4)}$$

Sentinel-1 data (dual-polarization C-band Synthetic Aperture Radar) were obtained for 13 months: from January 2018 to January 2019 (only January 2018 to March 2019 for Ascending mode due to an artefact) (Table 4.1). The images for the region include both from descending and ascending angles at a 10 m resolution, and the mean and standard deviation of VH (vertical transmission; horizontal reception) and VV (vertical transmission; vertical reception) bands were used for classification. Slope was calculated using the elevation data from the Shuttle Radar Topography Mission (SRTM) at a 30 m resolution (Farr et al., 2007). After adding the spectral and radar bands, NDVI, the texture index, and slopes, the images were scaled to a 20 m spatial resolution. The 20 m resolution was selected because of the 'red edge' bands (B5-7, B8A) in Sentinel-2 that cover narrow portions of the spectrum (<20nm wide), which are useful in classifying visually similar tree crops (Nomura and Mitchard, 2018).

The reference data required for training and testing in classification were obtained from Nomura and Mitchard, 2018 and by manual selection using high resolution (<2m) data viewed in Google Earth Pro. Most of the reference data for oil palm, rubber, and shrub were from high resolution images in Google Earth taken in 2018, with some exceptions going back to 2016, where those areas were checked for any changes with annual tree loss data from the Global Forest Change (Hansen et al., 2013). The reference data for bare land and water classes were taken from the Sentinel-2 cloud-free composite (November 2018 to January 2019) as well as from high resolution images in Google Earth from 2017 and 2018. The remaining class, "other" covers the largest areas in the region as it includes intact forests, mixed forests, betel & cashew nut plantations, and any other vegetation on the ground. Due to the lack of recent high resolution images in some areas, a few samples for the other class were taken from the images in 2015, which were checked with the Global Forest Change as well as the database from the Intact Forest Landscapes (Hansen et al., 2013; Potapov et al., 2008). The data were delineated as polygons and a stratified sampling method was used by randomly selecting 50% of pixels (20x20m) for training and testing. A total of 170,916 pixels were collected as reference data, including 32,945 pixels for oil palm and 13,384 pixels for rubber (See Table C.1 in *Supplementary materials*).

The oil palm concession area data were provided by OneMap Myanmar in October 2018 and used in the aggregated form (Centre for Development and Environment, 2018). Due to frequent changes, the data may include concessions that are cancelled or with unclear status. GIS data are digitised based on map information available in the land use permits: sketch maps, or maps drawn on old topographic one inch maps. OneMap Myanmar states that the data are provided as is, with all efforts made to produce a good dataset, but that the accuracy of the concession data is not guaranteed.

4.2.2 Classification

A machine learning algorithm, Random Forest was used to perform the classification (Breiman, 2001; Pal, 2005). Two parameters for the Random Forest classifier, the number of classification trees and the number of prediction variables per node were set at 100 and 4, respectively. Accuracy did not increase beyond 100 trees, so this was used, and the number of prediction variables were set at the square root of input variables (the square root of 17, rounded to 4) (Gislason, Benediktsson, and Sveinsson, 2006). After the classification, the pixels were filtered to represent the majority of the connected pixels at a 3x3 pixel neighbourhood window.

4.2.3 Accuracy

50% of reference data were randomly selected per class and set aside for testing (85,381 pixels). We chose this approach with a risk of over-estimation of the map accuracy due to auto-correlation, because alternative approaches have major disadvantages including preventing a classifier to produce the best results by withholding important training data (see Chapter 3.2.2 Dataset). We followed guidance from Olofsson et al., 2014 on calculating area-based uncertainty from datasets like these, and therefore believe our results are robust.

The overall accuracy, user's accuracy (UA), and producer's accuracy (PA) were calculated for two areas. The overall accuracy rate indicates the proportion of the area mapped correctly. UA and PA are the proportion of the area mapped as a particular class. UA is about the probability of a pixel in the output map being that class in reality, while PA is about the probability of a pixel in the test dataset of a particular class being correctly mapped (Olofsson et al., 2013).

4.2.4 Area estimation

The areas for each class were estimated by adjusting for classification errors and biases by using the reference data and a standard method (Olofsson et al., 2013). The classified pixels, after filtering, were counted for each class in the total area, and the proportion of the area mapped as the class was used to estimate the area for that class by multiplying it by the total area. Therefore, the final area estimates were based on the reference classification of each class and provided with 95% confidence intervals (See tables in *Supplementary materials*).

4.3 Results

We obtained an overall accuracy against independent test data of 94% when using satellite data to classify the region's land cover into six classes (See the Method section). The accuracy rates for oil palm and rubber ranged between 84-96% and 81-95%, respectively (See *Supplementary materials* for full error matrices, including user's and producer's accuracy). The uncertainty and bias inherent in the classification, estimated using independent data, was used to estimate bias-corrected area and 95% confidence intervals for each class (Olofsson et al., 2013).

In 2018, oil palm plantations (mature oil palm trees >4 years) covered approximately 75 kha (69-81 kha range at 95% confidence) of the Tanintharyi region (Table 4.2). Less than 70% (45-52 kha) of the oil palm plantations are within the concession areas, with approximately 25 kha planted outside (using the most recently available palm oil concession boundaries) (Centre for Development and Environment, 2018). By district, the southernmost district Kawthaung has the largest oil palm concession areas, with 63% of oil palm in the region planted in Kawthaung (Figure 4.2). The pattern of planting differed between the regions, with 84% of oil palm in Kawthaung planted within concession areas, compared to 34-35% in northern Dawei and Myeik districts. In total, only 6% of concession areas in the Myeik district were planted with oil palm, with the remainder made up of rubber (2%) and other trees (56%) (Figure 4.2). Dawei and Kawthaung districts had higher stocking rates, with 31% and 18% of concessions planted with oil palm, and 5% and 3% with rubber, respectively (Figure 4.2).

(ha)	Oil palm	Rubber	Other trees	Shrub	Bare	Water
Total	75,160	111,122	3,056,373	667,310	173,866	46,080
95% confidence	69,212-81,108	106,312-115,689	3,047,756-3,065,084	66,0851-67,3505	171,308-175,958	44,107-47,556
Within concession	49,276	7,771	195,246	60,853	9,013	2,547
95% confidence	45,119-52,932	7,392-8,007	194,523-195,833	59,897-61,494	8,723-9,142	2,456-2,630

Table 4.2: Area estimates by class (ha). Other trees include forests, tree plantations and tree-crops other than oil palm and rubber such as areca (betel nut) or cashew nut trees. Shrub includes grassland, open canopy, and young and low vegetation. Bare land includes sand. See Figure C.2 for examples.

The area shown in Figure 4.3(a) in the Myeik district contains large areas of unplanted concessions, compared to the area in Figure 4.3(b) in the Kawthaung district, where the oil palm plantations are concentrated. While some oil palm plantations located outside of concessions are an extension of or in close proximity to nearby concessions, others do not seem to have any relationship with concession boundaries. Expanding the concession area boundaries by 1 km, 17 kha still remain outside. It also appears that oil palm plantations tend to be found along

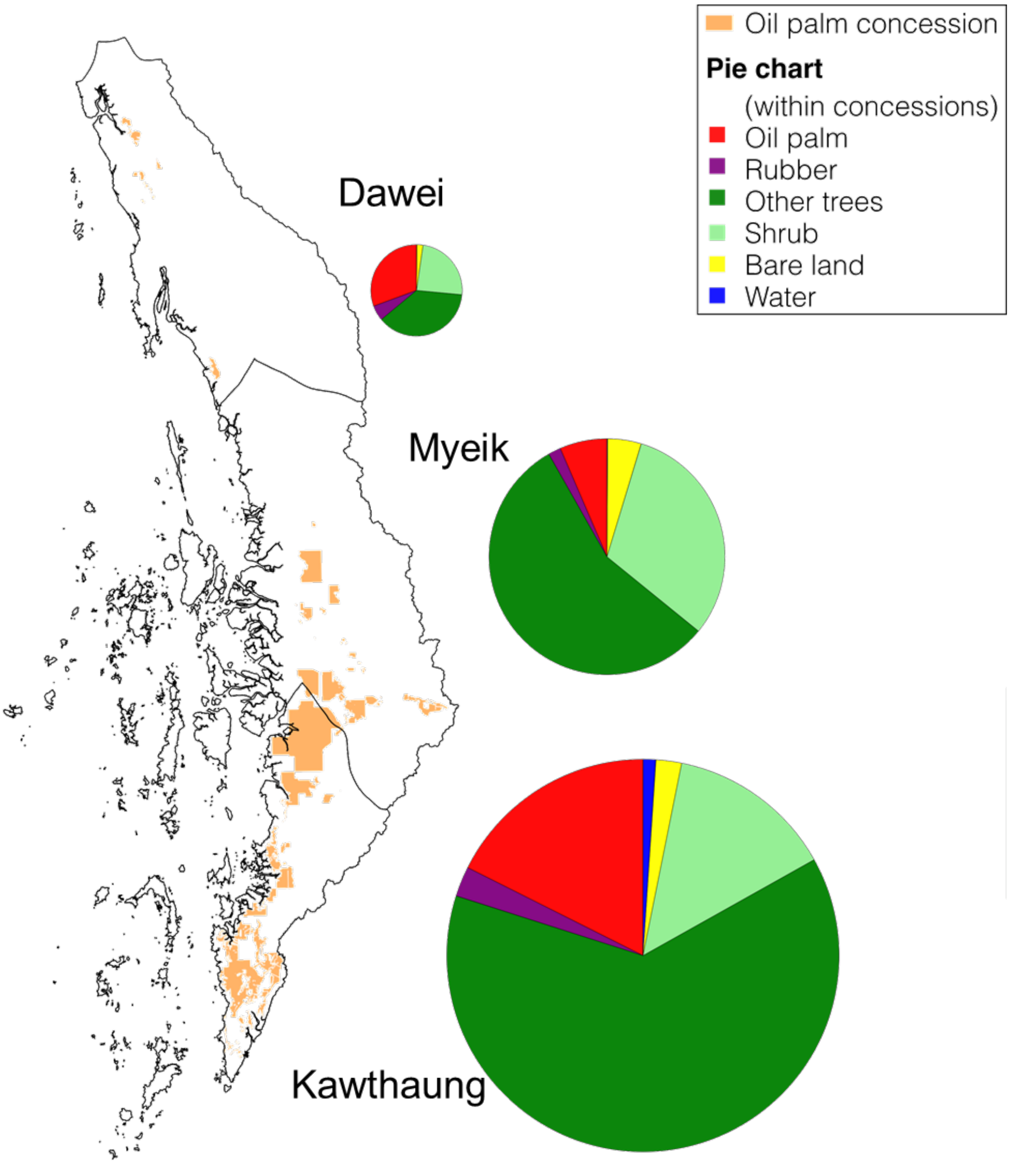

Figure 4.2: Planted area estimates by district. The pie chart shows land use of concession areas in each district, with the size corresponding to the size of total concessions.

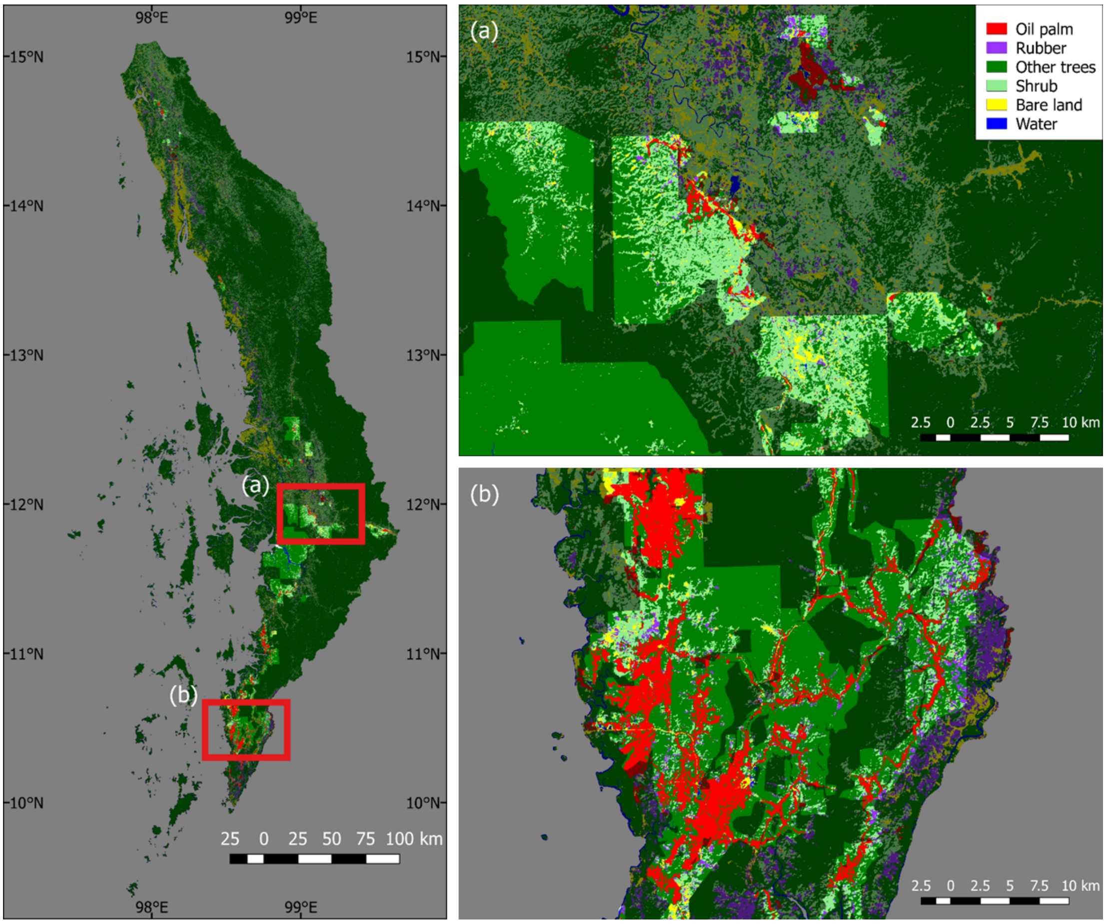

Figure 4.3: Classification results: map of the region by class (concession areas brighter)

the roads (Figure 4.3(b)). Some concessions overlap with proposed national parks (Tanintharyi National Park and Lenya National Park, both proposed in 2002). Within national park boundaries, approximately 4% of concessions (about 1,000 ha) are planted with oil palm or rubber plantations (2% each) (Figure 4.4), a considerably smaller proportion than 15% of concessions planted with oil palm in the region. Bare land covers about 6% of concession areas in the national parks, compared to 1% in the entire national parks. This leaves 65% (or 90% including shrub) of the concessions in the national parks which have not been planted with oil palm or rubber. The rubber plantations (mature rubber trees >6 years) account for approximately 111 kha in the region, which is 1.5 times larger

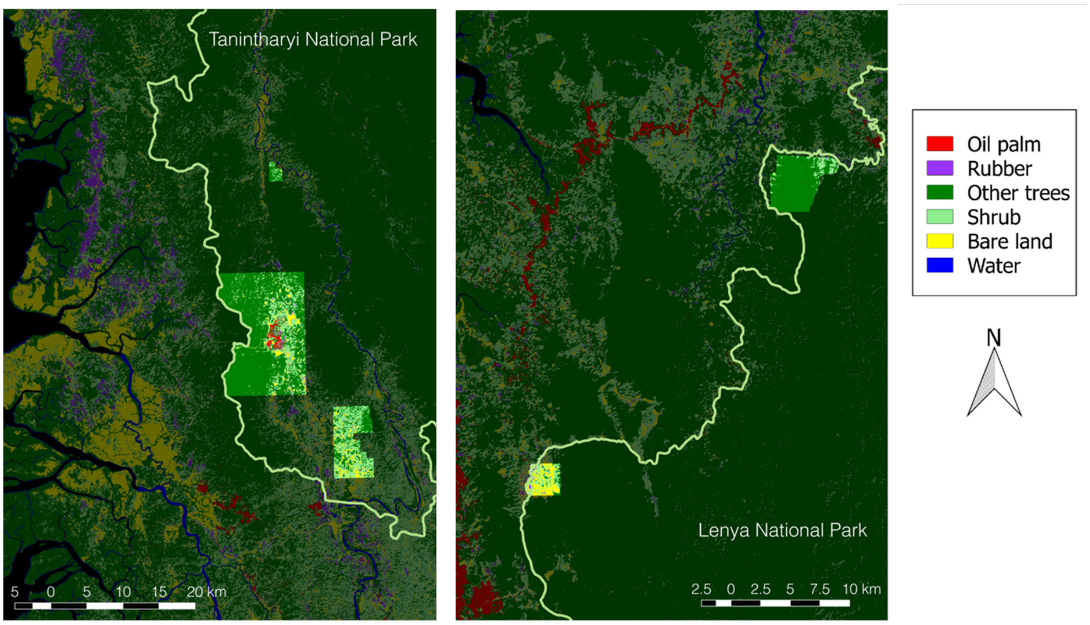

Figure 4.4: Classification results: concessions inside proposed national parks (concession areas brighter)

than the total areas of oil palm plantations (Table 4.2). The rubber is mostly located outside the oil palm concessions: only about 7 kha of this is found within the concessions, making up just 2% of oil palm concession area (Table 4.2, Figure 4.5). Most of these cases (72%) are in the southern tip of the Kawthaung district, where a large portion of the land is used for crops, and oil palm and rubber are often planted next to each other. In total, only 15% of concession areas are planted with oil palm while 60% (approximately 195 kha) are classified as "other trees" (this includes all other vegetation types, i.e. forests and tree-crops other than oil palm and rubber, such as betel or cashew nut trees (Figure 4.5).

4.4 Discussion

The results show that current oil palm plantations are much smaller than what has been reported to the government: 35% of concession areas (140 kha out of 401 kha) were reported to have been planted in 2015 (Baskett, 2016), while in our study 14

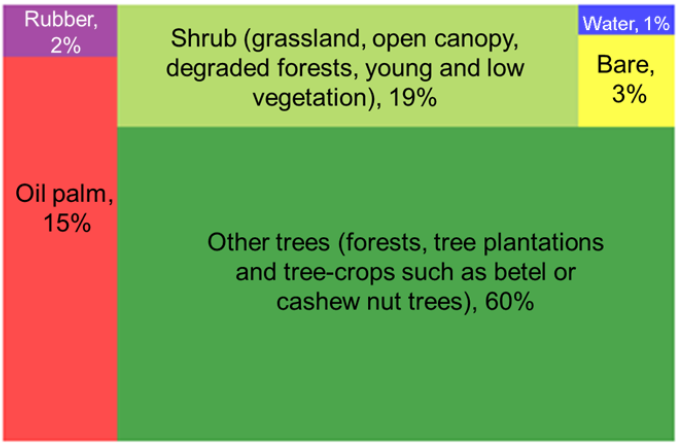

Figure 4.5: Land use of oil palm concession area. Other trees include forests, tree plantations and tree-crops other than oil palm and rubber such as areca (betel nut) or cashew nut trees. Shrub includes grassland, open canopy, and young and low vegetation. Bare land includes sand.

to 16% of the oil palm concessions (45-52 kha out of 324 kha) remain planted in the late 2018 and the beginning of 2019. Our estimates for oil palm plantations in the region are much smaller than in other studies (75 kha as compared to 136 kha (2016) by Connette et al., 2016 and 125 kha (2018) by Poortinga et al., 2019 (Connette et al., 2016; Poortinga et al., 2019). However, their methodologies differ from ours, most notably on the inclusion of red edge bands as well as the amount of reference data. We argue that other studies experienced difficulty in distinguishing oil palm from other tree crops or vegetation, which also resulted in lower accuracy rates.

A number of reasons could explain this discrepancy. Firstly, it could be partially explained by the 25 kha of oil palm that are planted outside of concession areas. If included, the total would become 23% of the current concession areas (69-81 kha). Secondly, the four-year difference between the two datasets may affect this difference: some old oil palm may have been cut down and plantations abandoned or replaced with other crops. This is possible given reports of declining oil palm business, especially in the north of the region, where the climatic conditions are less favourable (Baskett, 2016; Su Phyo Win, 2016; Saxon and Sheppard, 2014). This decline may be compounded by the limited number of processing facilities which are owned by a few companies, the availability of cheap oil palm imports, lower yields and poor quality of the palm oil (Baskett, 2016; Fujita and Okamoto, 2006). Finally, it is possible that there may be over-reporting of planted areas in the past, as the progress was previously monitored by the government ("General Thura Shwe Mann inspects oil palm cultivation projects in Taninthayi Division" 2004), and there may have been political reasons for the companies to over-report these figures.

While large areas of oil palm appear to have been planted outside of concession areas, the boundaries may have been unclear to companies, and some concessions have been cancelled or updated based on planted areas. Nevertheless, it is extremely important to clarify and demarcate the concession boundaries and start enforcing them in practice. Furthermore, there are oil palm concessions inside proposed national parks. The Tanintharyi National Park in particular has about 1,000 ha planted with oil palm and rubber. It is crucial to examine the suitability of remaining concession areas as oil palm plantations.

While the rubber plantations are estimated to cover a larger area than the oil palm plantations, our estimates (111 kha) are relatively consistent with the reported data (138 kha) in 2015-2016 and the study by Connette et al., 2016 (127 kha). The defoliation phase of rubber trees may have contributed to the difference, as our optical satellite data was collected during the dry season (November to January, when there are fewer clouds so optical satellite data is more likely to be available), which means some rubber could have been missed (Kenney-Lazar, 2016; Isabelle Vagneron et al., 2017; Nomura and Mitchard, 2018). The prevalence of rubber means that even if demand for oil palm slows, depending on the location, deforestation could still occur due to demand for rubber or other crops, as evidenced in the rubber planted in oil palm concessions.

Based on our study, rubber is the dominant crop in the region, while oil palm, although still the largest crop within the concessions, is planted much less than expected, leaving an extensive area available for other uses such as conservation or communities' livelihood needs.

The unconverted portions of the concessions represent a significant risk clearly, as they could legally be cleared at any time, but also an important opportunity for conservation and the global climate. These 195,246 hectares have an average aboveground carbon stock of 209.3 Mg C per ha per year (Avitabile et al., 2016), which means that clearing them would release at least 149.9 Tg CO_2e to the atmosphere, and likely more as this estimate ignores belowground and soil carbon pools. To put this in perspective, this is almost as much as the annual carbon emissions of the Netherlands in 2017, and over five times more than Myanmar's 2017 emissions from burning fossil fuels and cement manufacture (Quéré et al., 2018). Although these forests are included in Myanmar's Forest Reference Level under REDD+, the risks are calculated based on historical changes in forest cover at the national level. Clearly making space legally for the rescinding of such concessions could greatly reduce future emissions from the region and promote the protection of intact forests (UNFCCC, 2019; Nomura et al., 2019). This is especially relevant given the changing climate in this region, which could make Myanmar increasingly viable as a place to grow palm oil, just as Indonesia decreases in viability (Paterson et al., 2017).

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Chapter 5

Conclusions

5.1 Summary

The objectives of this thesis were three-fold: to understand the implications of current approaches to protecting forests by establishing emission levels; to propose practical methods to identify direct drivers of deforestation using publicly available data; and to identify whether any potential 'quick win' areas for conservation are available that are not being considered. These objectives were addressed in previous chapters by answering three research questions:

1. In Southeast Asian and neighbouring countries, how much (and what kind of) forests are covered under the international climate change mitigation mechanism, REDD+?

2. In Myanmar, can we accurately ascertain direct drivers of deforestation by classifying land after deforestation in these complex forest-agriculture-plantation landscapes?

3. In Myanmar, using the case study of the nascent oil palm industry, can we identify forest at risk and estimate the scale of potential areas available for conservation but currently set aside for future conversion?

In the following section, I answer based on the findings presented in Chapters 2-4, and highlight other key results from this work.

Chapter 2 (Nomura et al., 2019)

In this chapter, we first stress the distinction between forest areas defined using biophysical measures (i.e. land cover that meets minimum canopy percentage, forest area, and tree height thresholds) and the 'forest areas' used by countries to establish their forest reference emission levels or forest reference levels ('reference levels'), constrained further by land use and forest types.

- What constitutes a forest and which of the REDD+ activities are selected by countries?

Technical thresholds in defining forests (e.g. canopy cover, minimum area) were similar across the countries. However, a key difference was in the selected forest types: Indonesia alone excluded forest plantations in their forest definition; and three countries included rubber plantations as forests. In terms of activities, all countries, except Malaysia, included 'reducing deforestation' in their scope for REDD+. Two countries (Indonesia and Sri Lanka) did not include reducing forest degradation in their scope, potentially generating a perverse incentive to allow degradation to replace deforestation. As a result of these decisions, the forest areas used in their reference levels were reduced by 18 to 58% compared to the biophysical forest areas.

- How are the historical emissions calculated in the reference level submission? What are the implications of data sources and timeframe used?

The methods used for mapping, area estimation, MMU (minimum mapping unit) and change detection vary by countries. There are some common features, for example, six out of seven countries used Landsat data in some way. Several countries appear to have struggled to achieve high mapping accuracy (e.g. 74 and

75% from Cambodia and Sri Lanka, respectively). Many also lament a scarcity in data points (e.g. two data points to detect changes over a 10-year period by Nepal and Sri Lanka). Meanwhile, some countries (e.g. Cambodia and Indonesia) appear strategic in their selection of time period, choosing a period that gives a higher rate of loss than most other potential periods would have given, and thus potentially increasing their future payments under REDD+. For example, if Cambodia's reference period ended in 2010 rather than the year selected, 2014, the annual average deforestation rate would be 0.9% instead of 2.9%.

- What are the trajectories of forest cover change using the independent dataset 'Global Forest Change v1.4'? How different are they from the governments' estimates used to establish reference levels for the submissions to the UNFCCC?

Using the independent datasets, we show that biophysical forest areas declined across all seven countries between 2001 and 2016. My results demonstrate that for most of the countries in the region studied (6 out of 7), the decreases in biophysical forest areas were larger than reported and submitted to the UNFCCC. Despite this, two countries submitted data for forest areas that instead showed increases over this period, and established their reference levels based on this data. Therefore, even when countries' plans are compliant with REDD+ guidelines and implemented in full, REDD+ in these countries does not necessarily result in the reduction of forest loss, even if this is apparent based on the submitted data. In order for REDD+ interventions to effectively reduce emissions, identifying trends and drivers of forest loss should start with detecting changes at the biophysical level. In addition, countries should compare their reference levels using an independent dataset, and provide justifications for the differences if any.

Chapter 3 (Nomura and Mitchard, 2018)

To classify small patches of land and differentiate between similar tree crops with high accuracy (oil palm, rubber and betel nut plantations), I used Sentinel-2 data with a Random Forest classifier to map small patches totalling 13,330 ha. I used all 13 bands, normalised difference vegetation index (NDVI) and texture indices as input variables.

- Pixel-based machine learning classification of Sentinel-2 data can be used to map complex forest landscapes with high accuracy, as an alternative to computationally-intensive object-based classification methods.

With this approach, I was able to achieve an overall accuracy of 95% with a relatively small number of decision trees (30). Accuracy rates across classes were also consistently high, with more than 84.7% and 93.5% median accuracy rates for users accuracy (UA) and producers accuracy (PA). Among the three tree crop types, the highest average accuracy was 98.4% for rubber (PA), while the lowest average was 84.7% for betel nut (UA). The accuracy rates for oil palm ranged from 93% to 95.1%. It was not surprising that betel nut had the lowest accuracy, as it grows in very small patches (mostly < 0.5 ha) often on marginal land near communities, and is spectrally and structurally similar to oil palm: given this, achieving a UA of over 80% is more than expected. All of the analyses, except the collection of training data, were conducted using Google Earth Engine. This means that other users can easily learn to scale and apply the methods.

- Changes in land area by class from year to year can be confidently measured.

The area changes were estimated by considering the differences between two years (2017 and 2018), and compared to the spread of area values from the 1,000 iterations of the classification using different random subsets of the training dataset. It was concluded that there were likely changes in the area of a land cover class when there was no overlap in the interquartile ranges (25th and 75th percentiles, indicating the middle 50% of the distribution of area estimates) of the two sets of data. By running a large number of iterations, the results became more robust as the classification results are sensitive to each and every reference data point.

The results indicate that two study sites had contrasting trends; the east site had a relatively large increase in bare land and a decrease in rubber plantation area, while the west site had a large decline in bare land and increases in both oil palm and rubber plantations. These suggest that rubber plantations in the east were cleared for either replanting or for other use, but with no changes in oil palm plantation area, whereas oil palm and rubber plantations in the west expanded on previously bare land. In order to confirm these crops as drivers of deforestation, classifications need to be conducted prior to 2017 over multiple years; however, these results demonstrate that the methods can be used to make confident assessments of the change in area of different land classes.

Chapter 4 (Nomura, E. T. A. Mitchard, et al., 2019)

I used the method described in Chapter 3 over the whole of southern Myanmar, with the primary aim of assessing the area of oil palm concessions that had been left unplanted by the companies managing them.

- How can the method used in Chapter 3 be scaled up to classify a large area?

To classify the studied area (>4 million ha), I used a large amount of radar data (404 images from Sentinel-1 over 13 months) and slope from a digital elevation model (Shuttle Radar Topography Mission, SRTM) as variables to improve the classification. In addition, I increased the number of decision trees to 100 for the Random Forest classifier. All the data used for this analysis, except the concession areas, were publicly available. Similar to the previous method (see Chapter 3), the Google Earth Engine was used to conduct the analysis.

Maintaining the high spatial resolution of 20 m, an overall accuracy of 94%

was obtained against independent test data. The accuracy rates for oil palm and rubber ranged between 84-96% and 81-95%, respectively. This is lower than in the results in Chapter 3, but is not unexpected given the larger area, and thus larger variety of terrain, soil and vegetation types, covered.

- How much of the oil palm concession areas are currently planted or left unplanted?

Oil palm plantations covered approximately 75,000 ha (69,000-81,000 ha range at 95% confidence) of the region in 2018. Of this, less than 70% (45,000-52,000 ha) are within concession areas, with approximately 25,000 ha planted outside. 3% of oil palm concession areas were planted with rubber. As a result, there are about 200,000 ha of forests remaining within the oil palm concessions.

- Which crop is more dominant in southern Myanmar, oil palm or rubber?

Rubber plantations covered 1.5 times more area than oil palm plantations in the region. While oil palm is still the dominant crop within the oil palm concessions, rubber plantations may expand into oil palm concession areas in the future. This indicates that rubber is southern Myanmar's preferred crop, despite the government's initiative and investments to encourage oil palm to prevail.

- What are the implications for the forests remaining in current concessions?

Approximately 200,000 ha of forests within concession areas are unprotected and at risk of being converted legally to oil palm or rubber plantations. If protected, these offer a unique opportunity to to help Myanmar realise significant reductions in future emissions.

5.2 Implications

These results have important implications for policy makers and researchers, notably in the design of approaches and methodologies for protecting vulnerable forests in tropics, which have been set aside for clearance.

Recommendation 1: Detect changes at the biophysical level for REDD+

The process of identifying trends and drivers of forest loss should start with detecting changes at the biophysical level, using a small minimum mapping unit (less than or equal to 1 ha) for defining forest and forest change, and without initial exclusions based on land use classes. The participating countries should also be encouraged to disclose spatial data for forest plantations, so that researchers can exclude forest harvesting activities from deforestation.

Classifications and area estimates can be conducted with high accuracy at a large scale, using publicly available data and free API (Google Earth Engine), as demonstrated in Chapter 4.

Recommendation 2: Identify forests at risk inside agricultural concessions

It is not uncommon for agricultural concessions to be allocated without adequate environmental and social impact assessments. As a result, there are large areas of forests (including intact forests and peat swamps) included in the concessions in Southeast Asia. Global estimates of such forests are not available, however as discussed in Chapter 4, millions of hectares of forests were suspected to be at risk of conversion due to their land use class.

Using the method described and tested in Chapter 3 and 4, similar analyses should be conducted globally to identify forests at risk within other agricultural concessions.

Recommendation 3: Using available concession maps, detect and measure unplanted areas in countries beyond Southeast Asia

As of July 2019, 39 countries have submitted their forest emission reference levels (or forest reference levels) with the aim of receiving result-based payments under REDD+ in the future (Figure 5.1). Although my analysis was conducted for seven countries in Asia and the Pacific, the recommendations for better REDD+ planning are applicable to the remaining countries, not only in Asia but also in South and Central America and Africa.

Small farms and complex forest landscapes are also common in South Asia and Africa (See Chapter 3), where similar classification methods can be applied to identify direct drivers and estimate areas. Although agricultural plantations in South America are predominantly large scale, an increasing production of oil palm in the region (e.g. Colombia) means that differentiation among similar tree crop types may require higher resolution images and classifications with smaller minimum mapping units (MMUs) (e.g. Brazil's PRODES programme uses an MMU of 6.25 ha for detecting deforestation, larger than most agricultural holdings in Southeast Asia (UNFCCC, 2019)). The successfully scaled-up method described in Chapter 4 is applicable and can enhance such classifications. Using available concession maps (Figure 5.2), unplanted areas in other countries can be detected and measured globally.

Limitations and future research

The main limitations of this study are related to: 1) data; and 2) scale of classification. In terms of data, the following needs to be improved:

- Lack of forest gain data when assessing long-term trends of forest cover change: Although this has very limited impact on the current study, as the region has experienced far more loss than gain, in the future more and

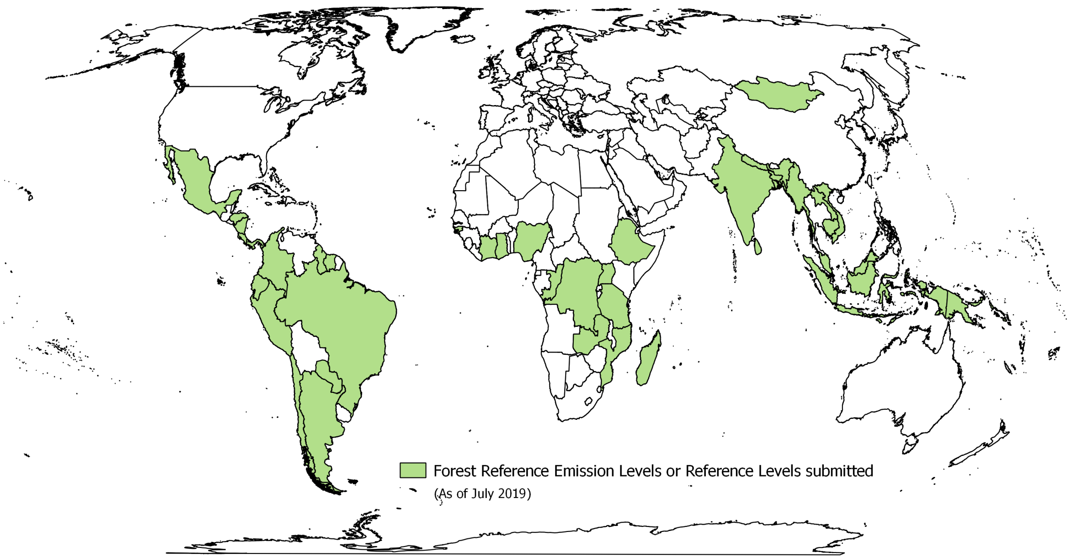

Figure 5.1: Countries that have submitted forest reference emission levels or forest reference levels. Data from UNFCCC, 2019

better forest gain data is desired, especially as reforestation and afforestation are seen as key and necessary activities to limit global warming to just 1.5 degrees (Masson-Delmotte, 2018), and that tropical countries have committed to reforesting 350 million hectares of forests by 2030 (*The Bonn Challenge* 2019).

- Limited or no availability of spatial data on national land use classes as well as plantations and agricultural concessions: this information is crucial for making policy recommendations. If forest plantation maps were available, tree loss due to harvesting cycle can be excluded from deforestation. Encouragingly, more data are becoming available: Global Forest Watch released plantation maps for 82 countries earlier this year; and more researchers are contributing to data transparency by providing maps for some countries.

- Ground-based surveys: Reference data are the backbone of reliable analyses. More researchers are using free high resolution images from Google Earth

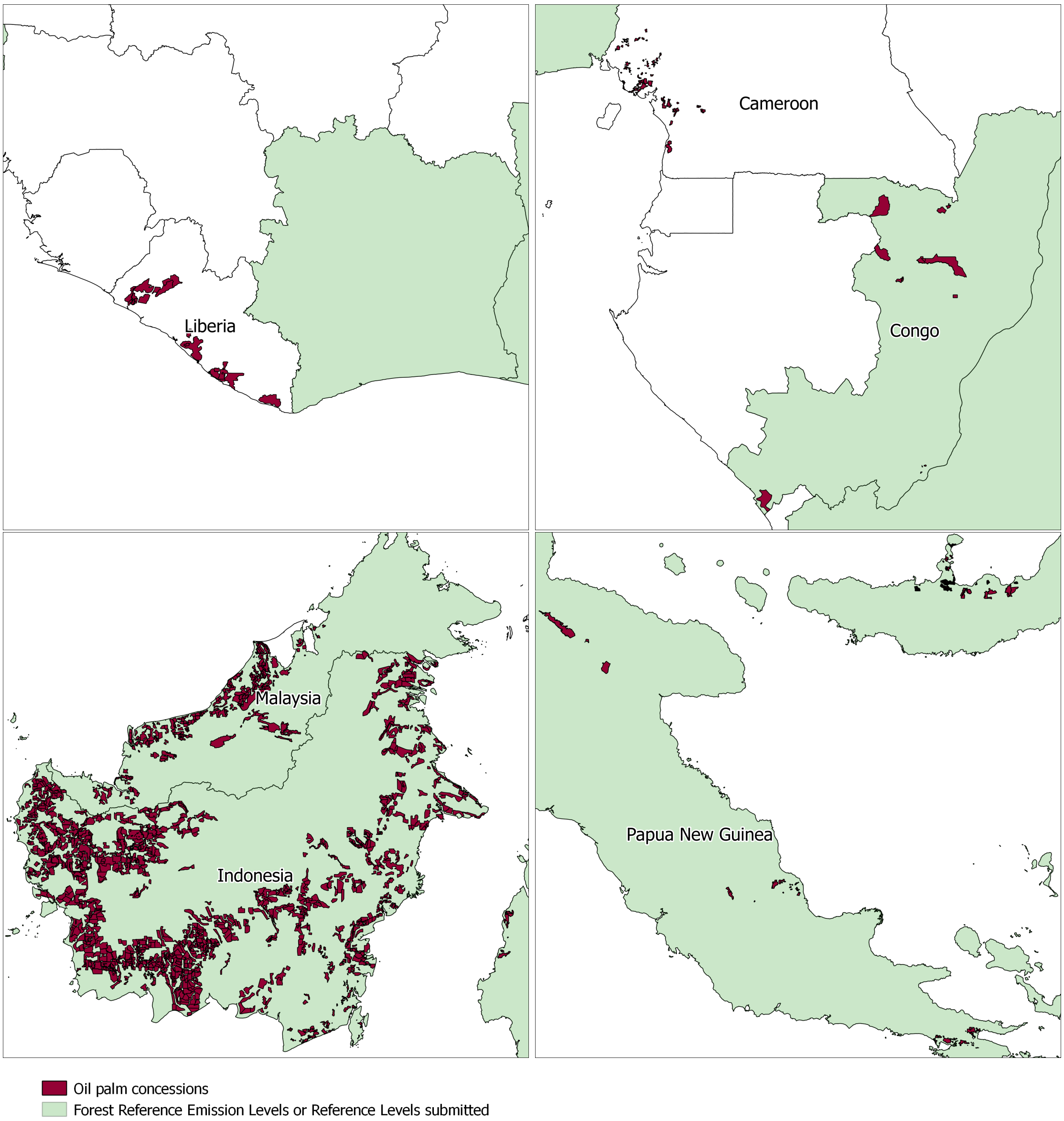

Figure 5.2: Oil palm concession maps available from the Global Forest Watch (*Global Forest Watch* 2019). The countries that have submitted reference levels are in green.

Pro for training and testing classifiers. However, the availability and temporal resolution varies by location. In collecting more data from the ground, recent developments include the use of mobile apps and crowd sourcing. More investments are needed to increase the generation and availability of ground data and scaling up the effort.

Lastly, classification exercises should be conducted at a local level to achieve better results. This is not only because of regional or local characteristics affecting the accuracy, but also differences in the type of drivers of deforestation and their behaviour. However, there is limited guidance on the size and type of area to be classified with a single classifier. Creating multiple classifiers will also slow down the process and create issues of different 'seams' between different areas, and country figures being made up by summing analyses that may have different error characteristics and even definitions. More research is desired to optimise the classification process in order to improve accuracy and efficiency.

Concluding remarks

My motivation for this PhD research came from my experience working with the governments in Southeast Asia on REDD+ from 2011 to 2016. Tropical forests are under tremendous pressure to serve an economic development agenda. At the same time, the willingness and desire to protect forests were also evident in consultations. Clearing forests for agriculture has not always resulted in improving the quality of life for communities in the affected areas. What was lacking was the reliable data for all the stakeholders to see and to make informed decisions. I believe that the transparency and timeliness of forest cover data can change the awareness and perception, leading to appropriate changes in policies and behaviour on the ground. This is why I emphasis using publicly available data and API, among which the Google Earth Engine is proven to be a powerful tool to provide access to a large amount of data and processing capability.

While my thesis found weakness in the global REDD+ process, its results provide grounds for optimism. I was able to demonstrate that we can classify complex tree-crops accurately using free satellite data, which had not been proven before. This is essential for REDD+ to succeed, because it enables us to assess direct drivers in a quantitative manner. I have further used these methods to discover a large area of remaining forests inside concession areas set aside for oil palm production in Myanmar's south: these forests could legally have been deforested, but have not. The good news is that these forests have survived, and it is crucial to recognise their role and keep them standing. Protecting unplanted areas will not affect the current production levels, making it easier to make a case for conservation. The results of my fieldwork in Myanmar helped balance my view on oil palm plantations in Myanmar, and ultimately led to the conclusion that reconsidering unused concessions for other land use, either for conservation or communities' livelihood, would be worthwhile. Myanmar could take this opportunity as a second chance and conduct environmental and social impact assessments for land use planning. As their impacts on emissions are significant if converted, protecting the remaining intact forests should be incorporated and prioritised as a climate change mitigation strategy.

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Appendices

Appendix A

Supplementary Materials for Chapter 2

Data

Please see https://bitbucket.org/nkeikon/erl/ for the code used for this study.

Activity	Explanation	Examples
Reducing emissions from deforestation	Deforestation is the conversion from forest land to non-forested land	Reduce the rate of forest loss due to industrial agriculture
Reducing emissions from forest degradation	Degradation is the human induced loss of carbon stocks within forest land that remains forest land	Reduce the rate and/or intensity of forest degradation due to unsustainable logging or fire
Conservation of forest carbon stocks	Refers to any effort to conserve forests	Strengthen and/or expand the protected area network. Also known as pure conservation zones, managed wilderness
Sustainable management of forests	Generally refers to bringing the rate of extraction in line with the rate of natural growth or increment to ensure near-zero net emissions over time	Increase area of forest land under sustainable management. Also known as sustainable yield management, community forest management
Enhancement of forest carbon stocks	Refers to (1) non-forest land becoming forest land and (2) the enhancement of forest carbon stocks in forest land remaining forest land (e.g. in the case of recovering degraded forests)	Increase area under reforestation and afforestation. Allow degraded forests to regenerate. Increase area of degraded forest under enrichment planting

Table A.1: Five REDD+ activities explained with examples (Lee et al, 2018; UN-REDD Programme, 2017)

	Scale	Scope				
		Reducing emissions			Removal of emissions	
		Deforestation	Forest degradation	Conservation of forest carbon stocks	Sustainable management of forests	Enhancement of forest carbon stocks
Cambodia	National	Forest land to other land types	Changes in forest subcategories	not included	not included	Other land uses to forest land
Indonesia*	National	Natural forest cover to other land-cover	Primary to secondary forest classes	not included	not included	not included
Malaysia	N/A	not included	not included	not included	Production forest area in Permanent Reserved Forest (increase in carbon stocks) and commercial harvest (decrease in carbon stocks)	not included
Nepal**	National	Forest to no-forest land	Fuelwood harvesting and unsustainable grazing and fodder collection practices	not included	not included	Afforestation reforestation, restoration
Papua New Guinea	National	Forest to non-forest land	Primary forest to disturbed forest	not included	not included	Any non-forest land to forest land
Sri Lanka	National	Forest to other land	not included	not included	not included	Afforestation/ reforestation
Vietnam***	National	Forest to non-forest land	Changes in forest types	not included	not included	Reforestation/ restoration

Table A.2: Scope and scale of national REDD+ in detail

*Indonesia includes primary and secondary forests of dryland, mangrove, and swamp.

**Nepal also includes the following as forests: "Young natural stands and all plantations established for forestry purposes which have yet to reach a crown density of 10 percent or tree height of 5 m are included under forest, as are areas normally forming part of the forest area which are temporarily un-stocked as a result of human intervention or natural causes but which are expected to revert to forest. This includes forest nurseries and seed orchards that constitute an integral part of the forest; forest roads, cleared tracts, firebreaks and other small open areas within the forest; forest in national parks, nature reserves and other protected areas such as those of special environmental, scientific, historical, cultural or spiritual interest; windbreaks and shelterbelts of trees with an area of more than 0.5 ha and a width of more than 20 m."

***Vietnam has the following three criteria: "1. An ecosystem of which the major component is perennial timber trees, bamboos and palms of all kinds of a minimum height of 5 meters (except new forest plantations and some species of coastal submerged forest species), and capable of providing timber and non-timber forest products and other direct and indirect values such as biodiversity conservation, environmental and landscape protection. New forest plantations of timber trees and newly regenerated forests of forest plantations are identified as forests if they reach the average height of over 1.5 meters for slow-growing species, and over 3.0 meters for fast-growing species and a density of at least 1,000 trees per hectare. Agricultural and aqua-cultural ecosystems with scattered perennial trees, bamboos or palms etc. will not be regarded as forests. 2. Having a minimum tree cover of 10% for trees which constitute the major component of the forest. 3. Having a minimum plot area of 0.5 hectares or forest tree strips of at least 20 meters in width and of at least 3 tree lines."

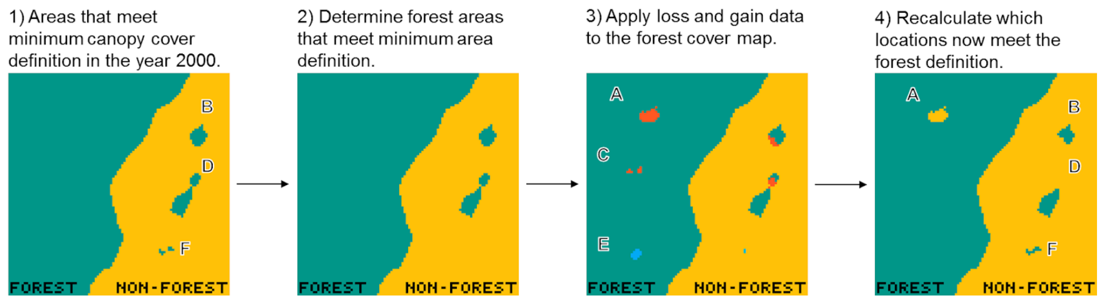


Figure A.1: Estimating tree cover, loss and gain in land cover with GFC dataset with illustrative examples

1. This location meets the forest definition in (1), and is subject to a large deforestation event that is recorded as reduced forest area in (4).
2. This forest patch is subject to a small deforestation event in (1), but remains large enough to still meet the forest definitions in (4).
3. Loss events that are smaller than the minimum mapping unit are not recorded as forest loss.
4. This forest patch has a small deforestation event, which leaves behind a patch of forest that is too small to meet the minimum area requirement. This is also recorded as loss.
5. Forest gain areas are occasionally reported in areas that meet the forest definition and are not subject to deforestation. These are not included.
6. A small forest gain event that connects two small patches of forest that do not meet the minimum area requirement can result in a larger gain being recorded.

	Minimum canopy cover (%)		Minimum tree height (m)	Minimum area (ha)	
	Forest area and loss	Forest area gain		Forest	Change (loss and gain)
a. Cambodia	10	50	5	0.5	5
b. Indonesia	30	50	5	6.25	6.25
c. Nepal	10	50	5	0.5	2.25
d. Papua New Guinea	10	50	5	1	1

Table A.3: Parameters for forest areas in Figure 2.5 (orange lines)

References

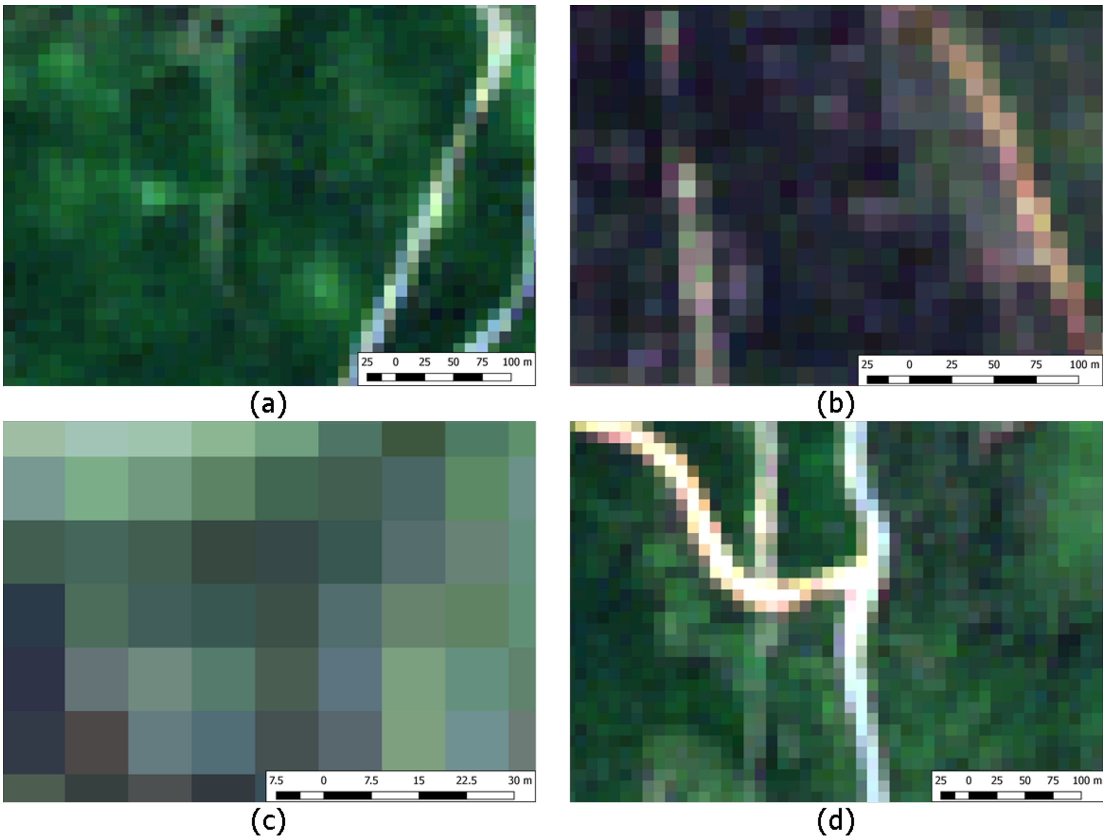
Lee, D., Skutsch, M., & Sandker, M. (2018). Challenges with measurement and accounting of the Plus in REDD+

UN-REDD Programme. (2017). REDD+ Academy Learning Journal Edition Two. Retrieved from https://www.unredd.net/documents/global-programme-191/redd-academy-3509/redd-academy-learning-journals/14931-redd-academy-learnign-journalcomplete-english.html

Appendix B

Supplementary Materials for Chapter 3

Figure 3.4 with Sentinel-2 images



Impacts of texture index

We tested the classification accuracy without the texture index (standard deviation of NDVI). While the texture index did help improve the accuracy, the differences were small (0.2% to 1.3% in increased accuracy).

	With texture	Without texture	Difference
Area A, 2017	95.0%	94.7%	0.3%
Area B, 2017	96.7%	95.4%	1.3%
Area A, 2018	95.7%	95.5%	0.3%
Area B, 2018	95.5%	95.3%	0.2%

Table B.1: Differences in classification accuracy due to texture index

Figure B.1 in the next page shows the spectral responses of an example classified map (random seed 0) to show the variation in spectral responses to the different classes. Note especially the differences between the tree crops in the red-edge and mid-infra red regions.

Google Earth Engine (GEE) code

Instruction: GEE registered users only; find the repository "users/nkeikon/S2/" under the "Reader" in the Script tab on the left.
https://code.earthengine.google.com/?accept_repo=users/nkeikon/S2

For cloning its Git repository, run the following command in a terminal: https://earthengine.googlesource.com/users/nkeikon/S2

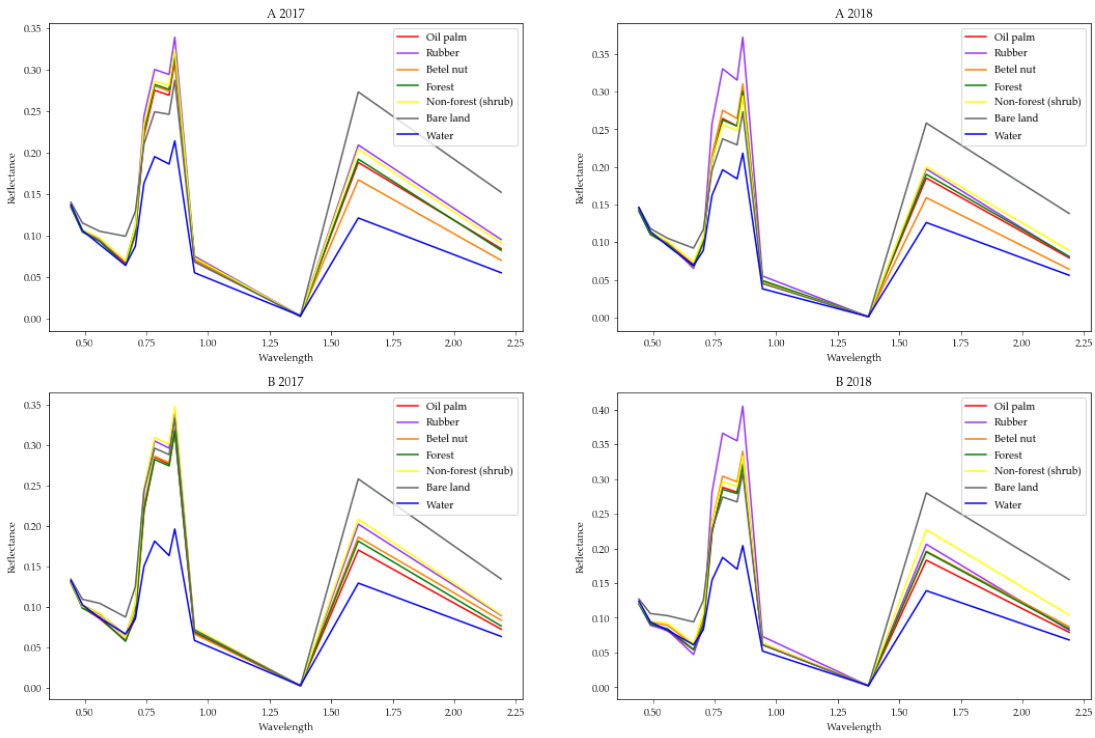


Figure B.1: Spectral bands per class.

```
/**** Start of imports. If edited, may not auto-convert in the playground. ****/
var roi = ee.FeatureCollection("users/nkeikon/RemoteSensing/Area_A"),
 palm = ee.FeatureCollection("users/nkeikon/RemoteSensing/palm_A"),
 rubber = ee.FeatureCollection("users/nkeikon/RemoteSensing/rubber_A"),
 betel = ee.FeatureCollection("users/nkeikon/RemoteSensing/betel_A"),
 forest = ee.FeatureCollection("users/nkeikon/RemoteSensing/forest_A"),
 nonforest = ee.FeatureCollection("users/nkeikon/RemoteSensing/nonforest_A"),
 bare = ee.FeatureCollection("users/nkeikon/RemoteSensing/bare_A"),
 water = ee.FeatureCollection("users/nkeikon/RemoteSensing/water_A");
/***** End of imports. If edited, may not auto-convert in the playground. *****/
/*//////////////////////////////////////////////////////////////
Below is an example of classification conducted for the study
"More than meets the eye: using Sentinel-2 to map small plantations
in complex forest landscapes" by Keiko Nomura and Edward TA Mitchard.
The default seed '0' is selected for random sampling in this example,
while the study conducted 1,000 classification runs (random seed: 0-999).
*/ //////////////////////////////////////////////////////////////

var areaName = 'A';
var year = '2017';
var startDate = '2017-02-01';
var endDate = '2017-02-28';
var randomSeed = 0;

// Display in the console
print('Area' + " " + areaName + ' ' + year);
var checkbox1 = ui.Checkbox('S2 least cloudy', true);
var checkbox2 = ui.Checkbox('NDVI', false);
var checkbox3 = ui.Checkbox('Texture', false);
var checkbox4 = ui.Checkbox('Classified', true);

checkbox1.onChange(function(checked) {
 Map.layers().get(0).setShown(checked);
});
checkbox2.onChange(function(checked) {
 Map.layers().get(1).setShown(checked);
});
checkbox3.onChange(function(checked) {
 Map.layers().get(2).setShown(checked);
});
checkbox4.onChange(function(checked) {
 Map.layers().get(3).setShown(checked);
});

print(checkbox4);
print(checkbox3);
print(checkbox2);
print(checkbox1);

//////////Sentinel-2 data//////////
var s2 = ee.ImageCollection('COPERNICUS/S2')
 .filterDate(startDate, endDate)
 .filterBounds(roi);

// Get the dates of available images
var list = ee.List(s2.aggregate_array("system:time_start")).map(function(d) {
 return ee.Date(d)
});
print('S2 images of the area during the study period', list);

// Get the cloud score of the images
var getCloudScores = function(img) {
 var value = ee.Image(img).get('CLOUDY_PIXEL_PERCENTAGE');
 return ee.Feature(null, {
  'score': value
 });
};

var s2clouds = s2.map(getCloudScores);
print('cloud score', ui.Chart.feature.byFeature(s2clouds));

// Sort images by least cloudy pixel %, select and rename the bands
var s2image = ee.ImageCollection('COPERNICUS/S2')
 .filterDate(startDate, endDate)
 .filter(ee.Filter.lt('CLOUDY_PIXEL_PERCENTAGE', 10))
 .sort('CLOUDY_PIXEL_PERCENTAGE')
 .filterBounds(roi)
 .map(function(img) {
  var t = img.select(['B1', 'B2', 'B3', 'B4', 'B5', 'B6', 'B7', 'B8', 'B8A', 'B9', 'B10', 'B11', 'B12'
  var out = t.copyProperties(img).copyProperties(img, ['system:time_start']);
  return out;
 })
 .select(['B1', 'B2', 'B3', 'B4', 'B5', 'B6', 'B7', 'B8', 'B8A', 'B9', 'B10', 'B11', 'B12'],
 ['aerosol', 'blue', 'green', 'red', 'red1', 'red2', 'red3', 'nir', 'red4', 'h2o', 'cirrus', 'swir1',
```

```
// Obtain the least cloudy image and clip to the ROI
var s2leastCloud = ee.Image(s2image.first());
var s2ROI = s2leastCloud.clip(roi);

var vizParams = {
 bands: ['red', 'green', 'blue'],
 min: 0,
 max: 0.3
};
Map.addLayer(s2ROI, vizParams, 'S2 least cloudy');

// Compute the Normalized Difference Vegetation Index (NDVI)
var red = s2ROI.select('red');
var nir = s2ROI.select('nir');
var ndvi = nir.subtract(red).divide(nir.add(red)).rename('NDVI');

var ndviParams = {
 min: -1,
 max: 1,
 palette: ['blue', 'white', 'green']
};
Map.addLayer(ndvi, ndviParams, 'NDVI', false);

// Compute standard deviation of NDVI as texture
var texture = ndvi.reduceNeighborhood({
 reducer: ee.Reducer.stdDev(),
 kernel: ee.Kernel.square(5),
});

Map.addLayer(texture, {
 min: 0,
 max: 0.25
}, 'Texture', false);

// Add NDVI and texture bands
var s2final = ee.Image(s2ROI).addBands(ndvi).addBands(texture);

// Add all the appropriate bands
var bands = ['aerosol', 'blue', 'green', 'red', 'red1', 'red2', 'red3', 'nir', 'red4', 'h2o', 'cirrus',
'swir1', 'swir2', 'NDVI', 'NDVI_stdDev'];
var s2finalWbands = s2final.select(bands);

// Scale the image to 20m
var s2classification = s2finalWbands.reproject(ee.Projection('EPSG:32647').atScale(20)).reduceResolution({
 reducer: ee.Reducer.mean(),
 maxPixels: 65535
});

//////////create training and verification data//////////
/* When conducting multiple runs, use:
   ee.List.sequence(seedMin, seedMax).map(function(n) {
   by setting min and max seed */

// Assign random column to sample
var n = randomSeed;
var randomPalm = palm.randomColumn('random', n);
var randomRubber = rubber.randomColumn('random', n);
var randomBetel = betel.randomColumn('random', n);
var randomForest = forest.randomColumn('random', n);
var randomNonforest = nonforest.randomColumn('random', n);
var randomBare = bare.randomColumn('random', n);
var randomWater = water.randomColumn('random', n);

// 50:50 for training and testing
var split = 0.5;

var trainingSample = randomBare.filter(ee.Filter.lt('random', split))
 .merge(randomForest.filter(ee.Filter.lt('random', split)))
 .merge(randomNonforest.filter(ee.Filter.lt('random', split)))
 .merge(randomPalm.filter(ee.Filter.lt('random', split)))
 .merge(randomRubber.filter(ee.Filter.lt('random', split)))
 .merge(randomWater.filter(ee.Filter.lt('random', split)))
 .merge(randomBetel.filter(ee.Filter.lt('random', split)));

var testingSample = randomBare.filter(ee.Filter.gte('random', split))
 .merge(randomForest.filter(ee.Filter.gte('random', split)))
 .merge(randomNonforest.filter(ee.Filter.gte('random', split)))
 .merge(randomPalm.filter(ee.Filter.gte('random', split)))
 .merge(randomRubber.filter(ee.Filter.gte('random', split)))
 .merge(randomWater.filter(ee.Filter.gte('random', split)))
 .merge(randomBetel.filter(ee.Filter.gte('random', split)));

// Get the values for training
var training = s2classification.sampleRegions({
 collection: trainingSample,
```

```
  properties: ['class'],
  scale: 20,
});

//////////classify and verify//////////
// Create the classifier
var classifier = ee.Classifier.randomForest({
    numberOfTrees: 30,
    variablesPerSplit: 4
  })
  .train(training, 'class');

// Classify the input imagery
var classified = s2classification.classify(classifier, 'classification');

// Create a palette to display the classes
var palette = ['ff0000', // palm 0 (red)
  '9933ff', //rubber 1 (purple)
  'FF7F00', //betel 2 (orange)
  '008000', //forest 3 (green)
  'ffff00', //nonforest 4 (yellow)
  'ffffff', //bare 5 (white)
  '0000ff', //river 6 (blue)
];

// Display the classified map
Map.addLayer(classified, {
  min: 0,
  max: 6,
  palette: palette
}, 'Classified');
Map.centerObject(roi, 15);

// Get a confusion matrix representing resubstitution accuracy
var trainAccuracy = classifier.confusionMatrix();
print('Resubstitution error matrix: ', trainAccuracy);
print('Training overall accuracy: ', trainAccuracy.accuracy());

// Sample the input to get validation data
var validation = s2classification.sampleRegions({
  collection: testingSample,
  properties: ['class'],
  scale: 20,
});

// Classify the validation data
var validated = validation.classify(classifier);

// Get a confusion matrix representing expected accuracy
var testAccuracy = validated.errorMatrix('class', 'classification');
print('Validation accuracy exported to "Tasks"');
//print('Validation error matrix: ', testAccuracy);
//print('Validation overall accuracy: ', testAccuracy.accuracy());

var visualization = classified.visualize({
  palette: palette,
  min: 0,
  max: 6
});

// Create a legend
var labels = ['Oil palm', 'Rubber', 'Betel nut', 'Forest', 'Non-forest (shrub)', 'Bare land', 'Water'];
var add_legend = function(title, lbl, pal) {
  var legend = ui.Panel({
      style: {
        position: 'bottom-left'
      }
    }),
    entry;
  legend.add(ui.Label({
    value: title,
    style: {
      fontWeight: 'bold',
      fontSize: '18px',
      margin: '0 0 4px 0',
      padding: '0px'
    }
  }));
  for (var x = 0; x < lbl.length; x++) {
    entry = [ui.Label({
        style: {
          color: pal[x],
          border: '1px solid black',
          margin: '0 0 4px 0'
        },
```

```
  }
  Map.add(legend);
};

add_legend('Legend', labels, palette);

////////// Calculate area by class//////////
var names = ['0 oil palm', '1 rubber', '2 betel nut', '3 forest', '4 non-forest', '5 bare land', '6 water'];
var count = classified.eq([0, 1, 2, 3, 4, 5, 6]).rename(names);
var total = count.multiply(ee.Image.pixelArea());
var area = total.reduceRegion(ee.Reducer.sum(), roi, 20);
print('Area by class (m2)', area);

//////////////export images and results/////////////
Export.image.toDrive({
  image: visualization,
  description: 'classifiedMap_colour' + '_' + areaName + year + '_' + randomSeed,
  region: roi,
  crs: 'EPSG:32647',
  scale: 20
});

Export.image.toDrive({
  image: classified,
  description: 'classifiedMap_raster' + '_' + areaName + year + '_' + randomSeed,
  region: roi,
  crs: 'EPSG:32647',
  scale: 20
});

var exportAccuracy = ee.Feature(null, {
  matrix: testAccuracy.array()
});
var exportAccuracyNumber = ee.Feature(null, {
  matrix: testAccuracy.accuracy()
});

Export.table.toDrive({
  collection: ee.FeatureCollection(exportAccuracy),
  description: 'AccuracyMatrix' + '_' + areaName + year + '_' + randomSeed,
  fileFormat: 'CSV'
});

//////////chart wavelengths by class//////////
// Chart S2 spectral bands
var classifiedImage = classified.select(['classification']);
var bands1 = ['aerosol', 'blue', 'green', 'red', 'red1', 'red2', 'red3', 'nir', 'red4', 'h2o', 'cirrus', 'swir1', 'swir2
var newImage = s2classification
  .select(bands1)
  .addBands(classifiedImage);

var wavelengths = [0.443, 0.490, 0.560, 0.665, 0.705, 0.740, 0.783, 0.842, 0.865, 0.945, 1.375, 1.610, 2.190];
var options = {
  lineWidth: 1,
  pointSize: 2,
  hAxis: {
    title: 'Wavelength (micrometers)'
  },
  vAxis: {
    title: 'Reflectance'
  },
  title: 'Spectra in Area' + ' ' + areaName,
  colors: ['ff0000', // palm 0 (red)
    '9933ff', //rubber 1 (purple)
    'FF7F00', //betel 2 (orange)
    '008000', //forest 3 (green)
    'ffff00', //nonforest 4 (yellow)
    'D3D3D3', //bare 5 (grey)
    '0000ff', //river 6 (blue)
  ]
};

var chart = ui.Chart.image.byClass(
    newImage, 'classification', roi, ee.Reducer.mean(), 20, labels, wavelengths)
  .setOptions(options);

print(chart);

// Chart indices
var bands2 = ['NDVI', 'NDVI_stdDev'];
var newImage2 = s2classification
  .select(bands2)
  .addBands(classifiedImage);

var xaxis = ['NDVI', 'Texture'];
```

```
var options2 = {
 lineWidth: 1,
 pointSize: 2,
 title: 'NDVI and Texture indices in Area' + ' ' + areaName,
 colors: ['ff0000', // palm 0 (red)
  '9933ff', //rubber 1 (purple)
  'FF7F00', //betel 2 (orange)
  '008000', //forest 3 (green)
  'ffff00', //nonforest 4 (yellow)
  'D3D3D3', //bare 5 (grey)
  '0000ff', //river 6 (blue)
 ]
};

var chart2 = ui.Chart.image.byClass(
  newImage2, 'classification', roi, ee.Reducer.mean(), 20, labels, xaxis)
 .setOptions(options2);

print(chart2);
```

Appendix C

Supplementary Materials for Chapter 4

Data, code, map

See https://github.com/nkeikon/tanintharyi.git for the code and reference data used for this study.

Cloud processing

Cloud score was computed by selecting the least-cloudy pixel from the collection of images over the three-month period (November 2018 - January 2019). The algorithm was originally written by Matt Hancher (Google) for Landsat and adapted for Sentinel-2 by Ian Housman (USDA Forest Service). The algorithm computes several indicators of cloudiness and takes the minimum value. See https://github.com/nkeikon/tanintharyi/blob/master/image_processing.js for the code.

Classification, reference data, and accuracy

The classification was conducted by separating the southernmost township, Kawthaung in the Kawthaung district (See Figure C.1), because its different characteristics meant that significant errors resulted when the two were considered together. The two maps were then mosaicked together for display purposes and the figures in the main paper, but accuracy and areas are considered separately below. The areas were estimated by correcting bias, thus adding up the number

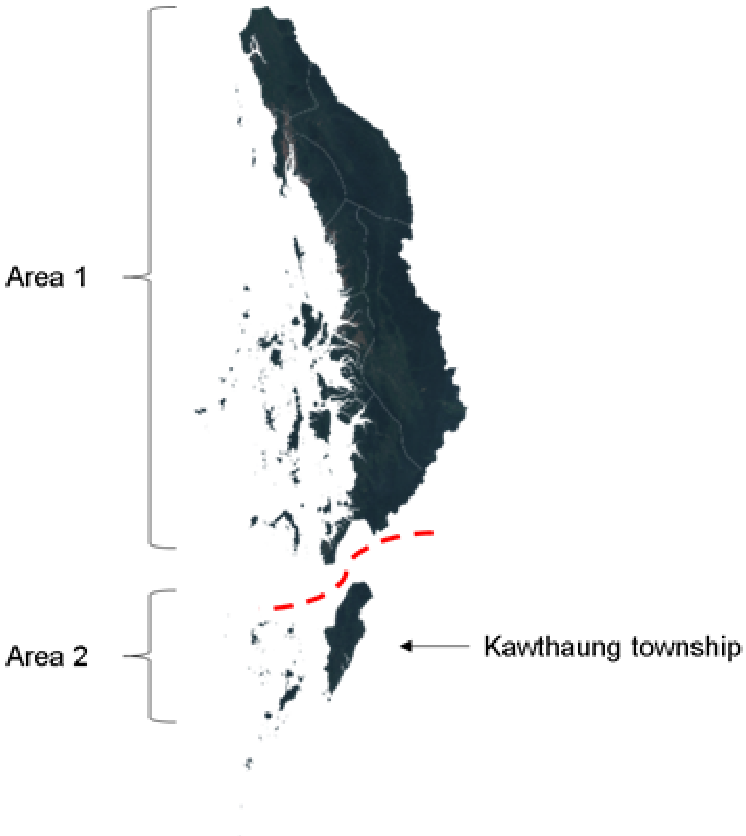


Figure C.1: Two areas for classification

of pixels for each class in the output map will not produce the same areas as those shown in the tables and in the text. See Table C.3 and C.4.

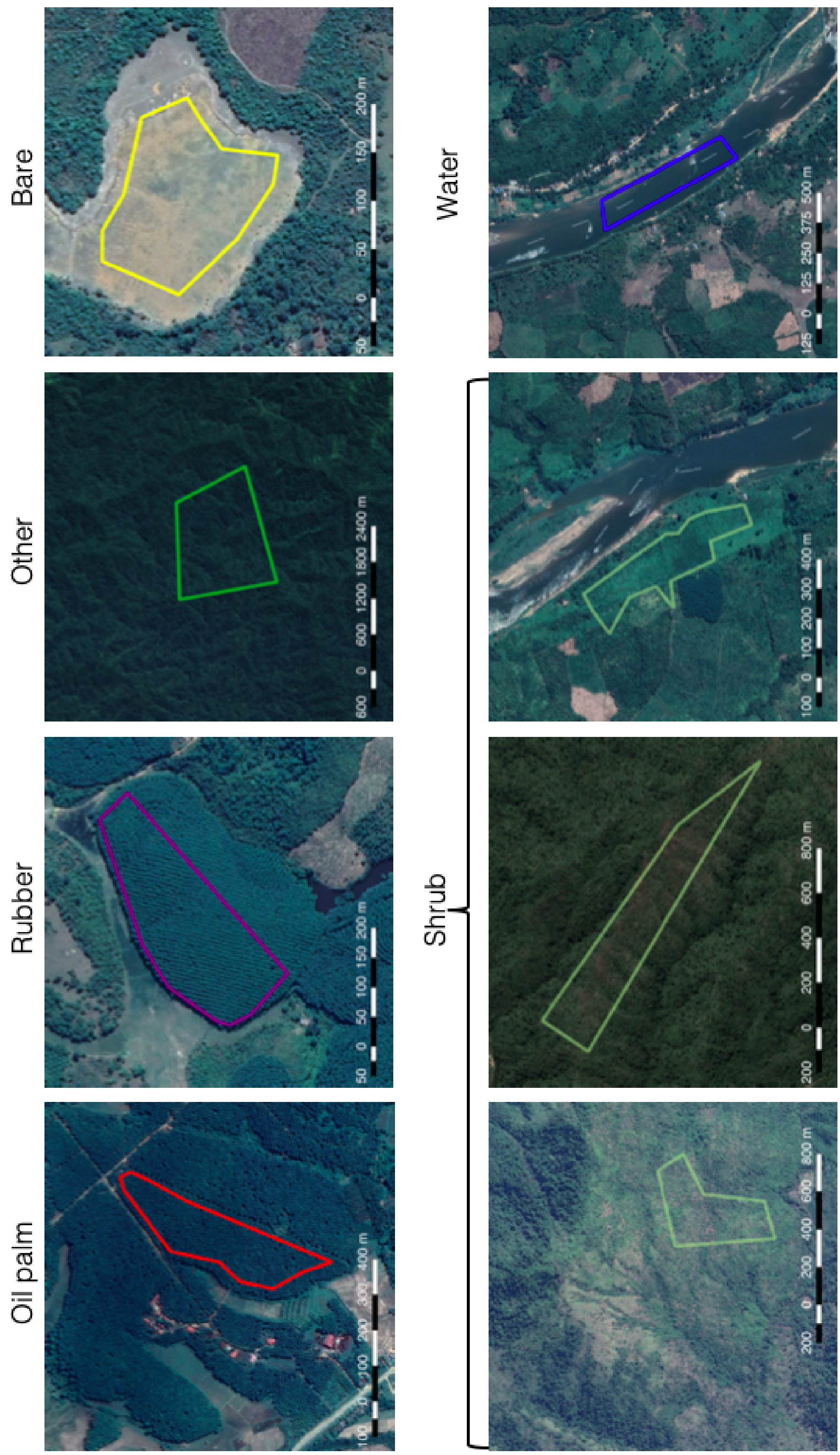


Figure C.2: Examples of reference data for each class. Images were delineated as polygons using QGIS 2.18.20. (Sources: Google Earth Pro 7.3.2.5776. Tanintharyi, Myanmar, DigitalGlobe 2019.)

	Area 1	Area 2	Total
Oil palm	21,564	11,381	32,945
Rubber	6,863	6,521	13,384
Other trees	56,520	37,866	94,386
Shrub	18,399	2,186	20,585
Bare land	1,301	1,083	2,384
Water	6,985	247	7,232
Total	111,632	59,284	170,916

Table C.1: Reference data (20x20m pixel count)

Area 1

Class	Oil palm	Rubber	Other	Shrub	Bare land	Water	User's accuracy	Producer's accuracy	Overall accuracy
Oil palm	9,815	28	956	44	1	0	91%	96%	94%
Rubber	6	2,790	246	413	0	0	81%	95%	
Other	445	29	27,394	520	0	0	96%	94%	
Shrub	2	91	567	8,500	11	0	93%	89%	
Bare land	0	0	0	22	649	1	97%	98%	
Water	0	0	0	3	2	3,487	100%	100%	
Total	10,268	2,938	29,163	9,502	663	3,488			

Area 2

Class	Oil palm	Rubber	Other	Shrub	Bare land	Water	User's accuracy	Producer's accuracy	Overall accuracy
Oil palm	4,882	27	862	16	4	0	84%	96%	94%
Rubber	0	3,017	187	29	4	0	93%	91%	
Other	224	70	18,520	29	2	0	98%	94%	
Shrub	1	194	54	868	1	0	78%	92%	
Bare land	0	9	8	5	531	0	96%	98%	
Water	0	0	8	0	0	117	94%	100%	
Total	5,107	3,317	19,639	947	542	117			

Table C.2: Error matrices

Error matrix, sample counts

		Reference						Total	Pixel	W_i
		Oil palm	Rubber	Other	Shrub	Bare	Water			
Map	Oil palm	21,044	1	12	2	-	-	21,058	711,381	0.007
	Rubber	7	6,401	11	24	1	-	6,444	1,881,140	0.019
	Other	500	210	56,177	369	-	9	57,265	75,163,984	0.753
	Shrub	37	236	241	17,962	34	9	18,520	16,705,549	0.167
	Bare	2	1	1	1	1,257	3	1,265	4,322,056	0.043
	Water	0	-	0	0	-	6,969	6,969	1,028,425	0.010
Total		21,590	6,849	56,442	18,358	1,292	6,990	111,520	99,812,534	1.000

Error matrix, estimates area proportions

		Reference						Total	Pixel	W_i
		Oil palm	Rubber	Other	Shrub	Bare	Water			
Map	Oil palm	0.0071	0.0000	0.0000	0.0000	0.0000	0.0000	0.0071	711,381	0.007
	Rubber	0.0000	0.0187	0.0000	0.0001	0.0000	0.0000	0.0188	1,881,140	0.019
	Other	0.0066	0.0028	0.7387	0.0049	0.0000	0.0001	0.7531	75,163,984	0.753
	Shrub	0.0003	0.0021	0.0022	0.1623	0.0003	0.0001	0.1674	16,705,549	0.167
	Bare	0.0001	0.0000	0.0000	0.0000	0.0430	0.0001	0.0433	4,322,056	0.043
	Water	0.0000	0.0000	0.0000	0.0000	0.0000	0.0103	0.0103	1,028,425	0.010
Total		0.0141	0.0236	0.7410	0.1673	0.0433	0.0106	1.0000	99,812,534	1.000
Area [pix]		1,409,392	2,358,747	73,961,429	16,698,297	4,326,248	1,058,420	99,812,534		
Area [ha]		54,794	91,211	2,868,109	646,200	167,452	41,099	3,992,501		
S(Area)		0.0003	0.0002	0.0005	0.0003	0.0001	0.0001			
S(Area) [ha]		2,710	2,129	4,071	2,970	980	681			
95% CI [ha]		5,311	4,173	7,980	5,822	1,920	1,335			
User's		100%	100%	98%	97%	100%	100%			
Producer's		49%	80%	100%	97%	100%	98%			
Overall		98%								

Table C.3: Bias-corrected area estimation and error matrix (Area 1) [1] [2]

Error matrix, sample counts

		Reference						Total	Pixel	W_i
		Oil palm	Rubber	Other	Shrub	Bare	Water			
	Oil palm	10,551	0	35	0	0	0	10,586	421,187 0.063	
	Rubber	20	6,296	26	101	8	0	6,451	492,918	0.074
Map	Other	750	186	37,768	76	5	39	38,824	4,945,663	0.741
	Shrub	11	16	4	2,010	8	0	2,050	532,723	0.080
	Bare	7	2	1	2	1,059	0	1,071	162,405	0.024
	Water	0	0	0	0	0	209	209	122,339	0.018
Total		11,340	6,500	37,833	2,189	1,080	248	59,191 6,677,236	1.000	

Error matrix, estimates area proportions

		Reference						Total	Pixel	W_i
		Oil palm	Rubber	Other	Shrub	Bare	Water			
	Oil palm	0.0629	0.0000	0.0002	0.0000	0.0000	0.0000	0.0631	421,187	0.063
	Rubber	0.0002	0.0720	0.0003	0.0012	0.0001	0.0000	0.0738	492,918	0.074
Map	Other	0.0143	0.0036	0.7205	0.0015	0.0001	0.0007	0.7407	4,945,663	0.741
	Shrub	0.0004	0.0006	0.0002	0.0782	0.0003	0.0000	0.0798	532,723	0.080
	Bare	0.0002	0.0000	0.0000	0.0000	0.0241	0.0000	0.0243	162,405	0.024
	Water	0.0000	0.0000	0.0000	0.0000	0.0000	0.0183	0.0183	122,339	0.018
Total		0.0780	0.0763	0.7212	0.0809	0.0246	0.0191	1.0000	6,677,236	1.000
Area [pix]		520,961	509,179	4,815,694	540,096	163,994	127,312	6,677,236		
Area [ha]		20,366	19,911	188,265	21,110	6,413	4,981	267,089		
S(Area)		0.0005	0.0003	0.0006	0.0003	0.0001	0.0001			
S(Area) [ha]		325	201	373	191	88	72			
95% CI [ha]		637	394	731	374	172	140			
User's		100%	98%	97%	98%	99%	100%			
Producer's		81%	94%	100%	97%	98%	96%			
Overall		98%								

Table C.4: Bias-corrected area estimation and error matrix (Area 2) [1] [2]

References

1. Olofsson, P., Foody, G. M., Stehman, S. V. & Woodcock, C. E. Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. Remote Sensing of Environment 129, 122–131 (2013).

2. Open source tutorials on remote sensing data analysis: https://github.com/kothawadegs/tutorials (Boston Education in Earth Observation Data Analysis, 2019).

Appendix D

Summary of Fieldwork in Tanintharyi, Myanmar

Introduction

In 1999, the Myanmar government designated the Tanintharyi Region as an oil palm development area. Located at the southern tip of the country, the area is considered suitable for oil palm plantations. The main purpose was to meet the domestic demand of palm oil, which was dependent on imports from Malaysia and Indonesia. The shortage of edible oil had been a serious issue in Myanmar, where residents in Yangon queued up to buy palm oil from 4 am (five hours before the opening hour) and there were reports related to confiscation of smuggled palm oil in 2002. The government's original target was to plant 500,000 acres of plantations by 2030, which was then later increased to 700,000 acres with a hope to export surplus palm oil. Initially, 19 companies (called "oil-palm growing entrepreneurs") from Yangon, were selected to conduct oil palm plantations. They were encouraged to cultivate palm oil and the land was allocated for free. Since then, more than 400,000 hectares, including villages and high conservation value forests as well as the territory of the Karen National Union (KNU), were allocated to 44 companies for oil palm plantations. Under the newly elected democratic

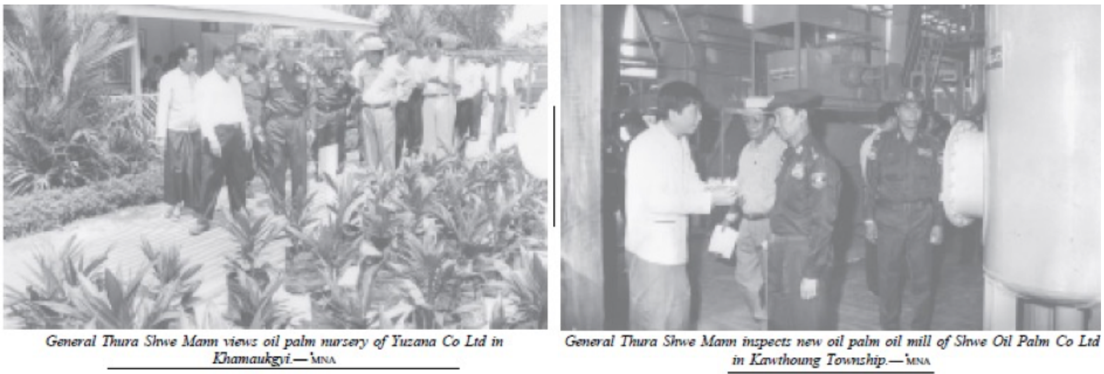


Figure D.1: General Thura Shwe Mann inspects oil palm cultivation projects in Tanintharyi (From The New Light of Myanmar, Mar 19, 2004).

Figure D.2: Daw Saw Yee (right), Assistant Director of the Department of Agriculture in Myeik

Figure D.3: U Thein Soe (second from the right), Assistant Director of the Department of Agriculture in Kawthaung and U Thant Zin (far left) from the district office who joined our visit to plantations in the district

government, conflicts with villagers have escalated and the concession areas are being challenged.

In March 2017, I visited 14 oil palm plantations in the Myeik and Kawthuang districts in the Tanintharyi Region of Myanmar, including the government-owned research plantation and one smallholder plantation in Kawthaung. My visits were made possible by the retired government officer, U Zaw Win, who introduced me to Assistant Directors of the Department of Agriculture that facilitated my visits to plantations in each district (Figure D.2 and Figure D.3). The main goal of the visits was to understand the current practices and challenges of oil palm companies. I also aimed to investigate the reasons behind the varying conversion rates (% of planted) and assess the future of the oil palm sector. Ultimately, this information will be used for land-use modelling in and around the oil palm concessions.

Observations regarding the interview method

All interviews were conducted in the interviewees' offices facing each other while sitting. The site managers often looked uncomfortable and several became nervous, because of the setting that had a sense of formality. This resulted in inconsistent answers at times. However, after the interview, as soon as we moved to their plantation or nursery, they were more relaxed and open. Asking questions while walking outside seemed ideal for interviewees as well as for the interviewer to obtain better information and garner more insights, but that made note-taking difficult, especially when there was no recording of the interview.

Interviewing inside (left) vs. outside (right)

Getting to the plantations

Before the concessions were allocated to the companies, the area was mostly covered with intact forests with limited access or infrastructure. While the companies were the first to build the roads, many plantation areas continued to be very remote. The region is undergoing rapid development with numerous road construction projects by the government. Our drivers used to work for the oil palm companies, so they were familiar with the roads, which was extremely important and made the visits much safer. They also often knew the site managers and other workers at the plantations. A few times, the companies granted us access even though they had not been informed of our visit on time.


Roads to the plantations

Methods

Semi-structured interviews were conducted with oil palm companies, government officials, and relevant NGOs. With the help of an interpreter, I asked about 10 to 15 questions to 12 companies, excluding the government research plantation and one company where we only went to their mill (Supplementary materials: Questions). In the Kawthaung district, an officer from the Agriculture Department accompanied us, which helped our visits tremendously (Figure D.3). Most of the interviewees were site managers, except for one company where I was able to interview the owner themselves. We were also able to speak to workers including nursery managers, harvesters, fruits collectors, and workers who cleared the land before planting.

After the interview, we went to see their plantations, nurseries, mills (four companies owned mills) as well as housing for workers, schools, and clinics, if they provide. We were not able to visit one of the companies' sites after the interview because of rain from the previous night that made access difficult. There were also two companies where we could not visit the nurseries because of the distance (far from the office and plantations).

Findings

About half of the companies we interviewed began operations in 1999 or 2000, which indicated that they were among the first 19 companies selected by the government. Most of the companies are involved in other sectors outside of agriculture, such as construction, machinery, finance, and fishery, among others. Three of the companies visited were either fully or jointly owned by foreign companies, including the one that their operation was being suspended due to conflict with communities.

There were considerable differences among companies in terms of the level of knowledge, interests, and willingness they had with respect to investing in the oil palm business. Some companies with concessions in the territory of the KNU experienced delays to their operation, because they had to negotiate with the KNU and agree on the terms. While logging for commercial timber was the main activity in most of the oil palm plantations during the first few years of operation and continued thereafter in many cases, such activities have declined because of the recent logging ban, the change of the government, and the increased awareness and pressure to protect forests. Consequently, at least one company that heavily

Figure D.4: Contour terracing

Figure D.5: Damage by elephants

relied on revenues from logging for the costs of their oil palm plantation is in serious financial distress and unable to continue their operation. However, there is inconsistent understanding and enforcement surrounding the legality of clearing forests within their concessions.

a. Land

Approximately 30 to 50% of each concession contained flat areas. There were many plantations built on steep hill slopes. Today, the importance of contour terracing is widely recognised and it is practiced by some companies (Figure D.4). However, the costs are perceived to be too high for the benefits they realise. Some companies use legume cover crops extensively to prevent soil erosion and enhance soil fertility. Parts of their plantations were almost fully covered by the cover crop, making oil palm trees less visible from afar in some cases (Figure D.6). At one plantation in Kawthaung, there were 25 elephants living in the area that destroyed oil palm trees and ate the crown part of the fruits (Figure D.5).

The region has a distinct dry season, which makes the proximity to water systems more important. Access to water is an issue in some plantations, which could lead to failure in the nursery (Figure D.7). One company built fishponds in their plantation in an effort to retain water (Figure D.8).

Figure D.6: Legume cover crops up close (left) and from far (right)

Figure D.7: Failed nursery

Figure D.8: Fishpond project

b. Productivity

The recent yields achieved by three companies were comparable to the average yields in Malaysia. The highest yield over the last five years was 9 tonnes per acre. According to one company, under ideal conditions, they could achieve a yield of 10 tonnes per acre. One of the key differences between the companies with higher yields (>6 tonnes per acre) and the rest (between than 2 and 5 tonnes per acre) was the use of fertilisers. Poorly performing companies either utilised too much fertilisers or no fertiliser at all. The difference in the amount of applied fertilisers per plant was as much as 3 kg per plant. Those that applied more fertilisers than necessary were suspected to have a personal relationship with the distributors. Smaller companies did not use fertilisers because of the costs, and their yield was approximately 2 tonnes per acre. Other key differences included concerns about climate change. The companies with higher yields attributed years of lower productivity to El Nino (e.g., 2015). The increased heat, longer dry season, and lack of rain were the last bottlenecks for the companies that managed all other aspects of their plantations well. One leading company built a system to water their plantation during the dry season in order to improve the yields (Figure D.10). There was no significant difference in the type of palm

Figure D.9: Application of limestone to increase the efficiency of fertilizers (by a company with high yields)

Figure D.10: Water system during dry reason

[!ht]

oil seeds used by companies. Historically, because of sanctions, Myanmar was only able to buy seeds from an agent in Costa Rica. Today, the seeds from Malaysia and Thailand are the most popular, followed by Costa Rican/Nigerian seeds (all seeds $1). Currently, there are efforts to improve Myanmar seed quality at the government plantation (300 kyat ($0.22)/seed) (Figure D.11 and Figure D.12). However, as a result of the lack of funding, the Myanmar seeds struggle to perform at the commercial level. Several companies that tried using Myanmar seeds indicated that they produced 1 to 2 tonnes less per acre than imported seeds and took two years longer to harvest. Furthermore, it seems unlikely that the government would be willing to increase funding for the research plantation. During the fieldwork, I encountered a French company, PalmElit, promoting their

Figure D.11: Government research plantation

Figure D.12: Myanmar seeds ("Myanmar Variety")

seeds to companies in Myanmar. According to PalmElit, their newly developed seed has been demonstrated to produce between 8 to 18 tonnes per acre.

c. Workers

Two-thirds of companies stated that they struggled to manage and retain workers for their plantations. Some plantations were difficult to maintain or harvest because of their distance from the nearby road. Most of the workers were migrants from other regions of Myanmar, which almost always include the Irrawaddy and Bago regions. The local communities near the plantations usually had their own means of living, such as from betel nut or rubber plantations, or shifting cultivation. Migrant workers tend to move from one company to another, and sometimes to Thailand (300 baht ($8.79)/day). Some companies did not allocate enough money to hire workers on time. Hard work and heavy rain were among the other reasons. Worker wages are based on the type of work and outputs. Typically, the daily wage ranged from 4,000 to 6,000 kyat ($2.93 to $4.39). The lowest paid work was performed by collectors, who take fruits from the trees to nearby roads. They are usually women and are paid about 2,000 kyat ($1.46) per day, which is lower than the minimum wage of 3,600 kyat ($2.63) per day. Not all plantations require the work of collectors - it depends on proximity to the roads. Some companies hire hunters or install shields to protect plants from


Figure D.13: Workers harvesting and collecting fresh fruit bunches (FFBs)


Figure D.14: Workers' names are written on leaves to weigh FFBs

Figure D.15: Worker with his handmade axe to clear land

Figure D.16: Workers making shields for plants to protect from rats and porcupines

rats and porcupines (Figure D.16). Planting is paid according to the number of plants (e.g. 300 to 800 kyat (\$0.2 to \$0.6)/plant), while harvesting is paid based on weight or bunches (5,000 to 12,000 kyat (\$3.66 to \$8.78)/ton). Workers carve their names on leaves, which is placed on the top of the fruits on the side

Figure D.17: Housing for workers

of the road. According to a worker in Kawthaung, his daily wage works out to be roughly 6,000 kyat ($4.39). Clearing, ploughing, weeding, and leaf cutting are paid on a per acre basis (e.g., 100,000 kyat ($73)/acre for clearing, 10,000 to 30,000 kyat ($7.32 to $21.96)/acre for the other work). Permanent staff is paid monthly (170,000 to 200,000 kyat ($124 to $146)/month).

Most of the companies provide housing, electricity, and water for workers for free (Figure D.17). There was one company that also supplied food, though others sold it at discounted prices. Several companies built markets, import food, or provide transportation to nearby markets (Figure D.18). This was necessary because of the location of the plantations. Clinics, schools, and kindergartens were also provided by the companies (Figure D.19, Figure D.21, and Figure D.21), and in the case of the clinics they were not only available for their workers, but also for the villagers nearby. Some companies were active in corporate social responsibility (CSR) by building recreational facilities for their workers or wells for villages (Figure D.22 and Figure D.23).

d. Price

Two of the large companies interviewed owned sizable oil palm mills, where other companies sold their fresh fruit bunches (FFBs) at the prices set by those two companies. Palm oil (crude palm oil and palm kernel oil) from the mills were

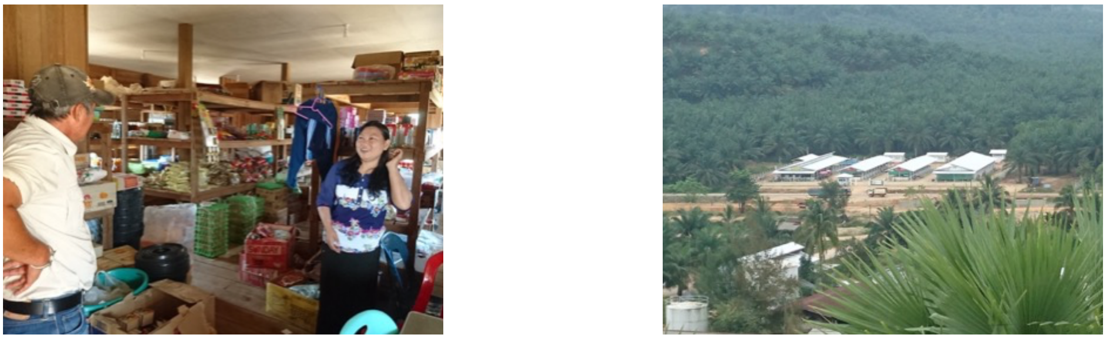


Figure D.18: Shops and markets inside plantations

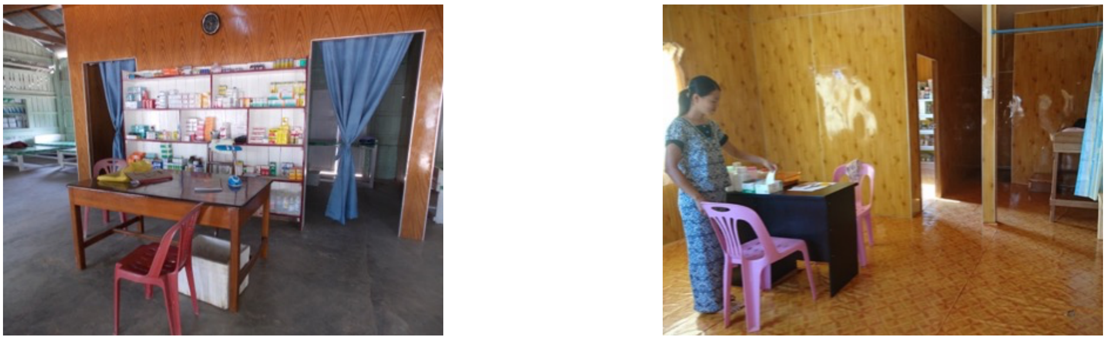


Figure D.19: Clinics

Figure D.20: School

Figure D.21: Kindergarten

Figure D.22: Football field

Figure D.23: A well for villagers

Figure D.24: Palm kernel

Figure D.25: FFBs in an oil mill

transported to the refineries in Yangon by ship. At smaller mills where they did not process kernel oil, they exported palm kernel to Thailand (Figure D.24).

At the time of the interviews (March 2017), the companies were selling their FFBs at 100,000 to 120,000 kyat ($74to88$) per tonne. They tended to believe that the prices were always higher in one company than the other, but that was not the case at the time of the interview. Because of the monopoly of the mills and lack of transparency in pricing, there was resentment among the companies and almost all of them desired to build their own mills in the future. One company in Kawthaung that may have been able to build a mill in the near future, but they were seeking for more investors for their project.

Despite the current low prices of imported palm oil, the companies were positive about the industry's future. This confidence stemmed from the strong domestic as well as foreign demand on palm oil. In addition, the palm oil

Figure D.26: Karen villagers going through the plantation to hunt

Figure D.27: Shifting cultivation by villagers inside the concession

industry in Myanmar is currently benefiting from the lack of standards on edible oil products, which allows them to blend palm oil with peanut oil at the refineries in Yangon. This practice was also reported by FAO in 2009.

e. Conflict

All the companies interviewed wanted to expand their plantation areas and many had targets in acreage. Some of these targets were set in order to make a case to build a mill. However, the companies in the Kawthaung district became more cautious about clearing forests within their concession areas, and some companies were instructed not to clear forestland by the government. Furthermore, a few concessions in the district, which had not been planted and were in the land administered by the Forest Department, were cancelled. However, there were companies that experienced no problems when clearing forests and some were able to negotiate and obtain more land from the Forest Department. This appeared to depend on the location of the plantation, the company's relationship with the villagers, government agencies, and the KNU. A few large companies had exhausted their concession areas, and they are now primarily replanting.

Conflicts with villagers seem to be on the rise because of the limited availability of vacant land as well as the increase in migration from within and outside of the Tanintharyi region. The existence of the road also seems to attract more movement to the plantation areas. Depending on the location, refugees and internally displaced people, who left their village in the 1990s due to the fight between the KNU and the Myanmar Armed Forces, are returning since the cease-fire agreement was signed. It is very common to see many villages inside the plantations, but conflict takes place when villagers want to plant rubber or betel nuts, where the company was planning to plant oil palm. Some companies have started suing villagers, however the regional government expressed concerns about such actions and discouraged others from following. Interestingly, one company was now actively purchasing land in their concession from villagers conducting shifting cultivation (Figure D.27).

The regional government is currently trying to address the land conflict by identifying unplanted areas and allocate them to villagers. They started the assessment in the north of Tanintharyi, in the Dawei district, and were expected to continue this in two other districts in the south. There is growing dissatisfaction among companies toward the regional government, yet in light of changing politics and the increased attention of NGOs and the media to oil palm companies, the companies are reluctant to escalate conflicts with villagers.

f. Sustainability

Currently, there is no reporting of environmental management plans by the companies to the government. As all the companies started their operations before the current Environmental Impact Assessment (EIA) procedure was introduced, no company has conducted EIA. One company noted they were planning to conduct EIA on their mill, because some issues were pointed out by the Environmental Conservation Department. Other companies managed environmental issues by responding to complaints of murky water or the use of fertilisers.

The Roundtable on Sustainable Palm Oil (RSPO) was not well understood by many companies, although all the companies interviewed attended FFI's workshop on RSPO in 2014 and 2015. A few companies had a good understanding of RSPO, though were reluctant to comment. One of the concerns seemed to be that the RSPO would not consider Myanmar-specific circumstances in the definition of sustainability.

g. Mapping

The regional government is currently trying to address the land conflict by identifying unplanted areas and allocate to villagers. They started the assessment in the north of Tanintharyi, the Dawei district, and expected to continue to other two districts in the south. At this point, it is not clear when the assessment for the Myeik district will take place or if it will continue to the Kawthaung district.

Example of an UAV image (left) View of plantations (right)

Next step

The next fieldwork will be conducted in March next year as planned. The main purpose is to collect data on the changes in tree cover and obtain updates on land conflict and land use in concession areas.

Discussion

- A small number of companies, including all the well-performing ones, have run out or are about to run out of land for new plantations. At the same time, at least about one third of all the companies in the sector seemed inactive. However, only two of the companies interviewed experienced mergers and acquisitions (M&A). It seems unlikely that M&A activity will increase in the sector in the near future, unless there is an increase in milling capacity or in the costs of keeping the land for inactive companies. One company commented that it was much cheaper to purchase land from the government than from other companies.

- The Department of Agriculture in the two districts did not think that the 700,000 acre target was achievable. The companies were also aware that not all the concession areas can be planted. Revising the target from one that was acre-based to yield-based could improve the sector's performance. It may also create an entry point for dialogue between the regional government and the companies.

- Smallholder plantations can be one way to resolve land conflicts with villagers and alleviate poverty. At the time of the visits, however, farmers preferred betel nut and rubber plantations because of the higher prices. Some smallholders that planted oil palm were not actively managing their oil palm plantation and they did not harvest if they were busy with other crops.

- More investments (both foreign and domestic) into the agriculture sector are sought by the central government, as reflected with the intention of the new Investment Law. However, the current risk is too high for investors, due to the uncertain regulatory environment, conflicting information about the rules and regulations, and inconsistent enforcement. A strong leadership to regulate the sector and ensure the sustainability of palm oil production will not only lower the risk but also attract more investments.

- Although many companies struggled with worker retention, labour costs were considered cheap. Most of the companies continued to clear land and plant new oil palm, while their existing plantations were often not well maintained, resulting in lower productivity.

- While land taxes were extremely low (1,000 kyat/acre), the production tax was calculated based on yields. There is a clear disincentive to achieve and/or report higher yields.

- The industry association is not active, but the companies have good relationships with each other. As many of them are experiencing similar issues, gathering information to find solutions by revitalizing the association or the establishment of a platform can be considered. This will also help bridge the knowledge gap between the companies.

Supplementary materials: Questions

1. Please tell us the history of this plantation

2. What kind of seeds do you use? How many plants do you have in your nursery?

3. What is your recent yield?

4. How much of your land is flat or suitable for oil palm? How do you manage the dry season and steep slopes?

5. How much do you plant every year? When is the last time you planted? Do you plan to plant more?

6. What kind of fertilizers, pesticide, and fungicide do you use? Where do you import from? How much do you apply?

7. Do you have any issues with animals in the plantation?

8. Where are your workers from? How much do you pay? How do you recruit them?

9. What is the most difficult thing about managing the plantation?

10. Do you share information with other oil palm companies, or the industry association?

11. Do you have CSR (corporate social responsibility) programs?

12. Do you have Environment Management Plan (EMP)? Have you conducted Environment Impact Assessment (EIA)? Do you know RSPO?

13. Do you have smallholder programs?

14. What kind of support do you expect from the government?

15. What do you think about the future of the plantation or the industry? What do you think about foreign investors?